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Water-Energy Nexus: Benchmarking the Energy Efficiency of Drinking Water Treatment Plants Accounting for Heterogeneity

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ABSTRACT

The assessment of energy efficiency in water facilities is receiving increasing attention as a key strategy in the transition toward an energy-neutral urban water cycle. This study evaluates the energy efficiency of 146 drinking water treatment plants (DWTPs) in Chile by applying a latent class stochastic frontier analysis (LCSFA) to account for both observable and unobservable sources of heterogeneity. Unlike traditional models that assume homogeneity across units, the LCSFA approach identified two distinct groups of DWTPs with significantly different operational characteristics, pollutant loads, and efficiency profiles. Group 1 exhibited an average energy efficiency score of 0.534, while Group 2 showed a significantly higher average of 0.737. In Group 1, efficiency scores estimated under the pooled frontier are higher than those obtained from the latent class model for 73% of DWTPs, whereas in Group 2 the pooled frontier yields lower efficiency scores for 58% of plants. The analysis also revealed substantial energy-saving opportunities. Group 1 facilities could reduce energy use by an average of 0.112 kWh/m^3, compared to 0.044 kWh/m^3 in Group 2. These findings demonstrate the importance of adopting heterogeneity-aware methods for fair and accurate benchmarking. The study offers methodological innovation and practical insights for regulators and utility managers aiming to design targeted energy efficiency interventions and performance-based incentives in the water sector.

1 | Introduction

Access to drinking water is a basic human right, a principle reinforced by Sustainable Development Goal 6, which aims to achieve universal and equitable access to safe and affordable drinking water for all by 2030 (United Nations 2010, 2015). In this context, energy is an essential input for water utilities, enabling the treatment and distribution of drinking water (Sowby 2023). Globally, approximately 2.5% of total energy consumption is attributed to drinking water supply systems (Yateh et al. 2024). This has significant economic and environmental implications, as energy costs can represent up to 40% of a utility's operating expenses (Sowby and Burian 2018). Moreover, previous studies have quantified the greenhouse gas (GHG) emissions associated with the energy used in water provision (Nault and Papa 2015; Smith et al. 2016; Bukhary et al. 2020). For example, GHG emissions associated with water supply in 10 major United States cities have been found to range from 21 to 560 g CO_2 equivalent per cubic meter of water supplied (Sowby and Capener 2022).

While all stages of drinking water provision—namely raw water abstraction, treatment, and distribution—require energy, the greatest share of energy consumption is typically associated with the removal of pollutants in drinking water treatment plants (DWTPs) (Zhang et al. 2017). Within the framework of the water–energy nexus, two main analytical approaches have been used to study energy use in DWTPs. On one hand, several studies have focused on quantifying the energy consumed during the production of drinking water (Santana et al. 2014; Lam et al. 2017; Chini and Stillwell 2018) expressed in kWh/m^3. These studies highlighted that energy use in DWTPs is influenced by a variety of factors, including the source of raw water, the type and concentration of pollutants, and the treatment technologies employed (Bukhary et al. 2020; Amaral et al. 2025). On the other hand, to better integrate the quality of both raw and treated water into performance assessments, alternative studies have focused on estimating the energy efficiency of DWTPs (Molinos-Senante and Guzmán 2018; Ananda 2019; Maziotis et al. 2023). This approach enabled a more comprehensive evaluation of energy performance by accounting for both inputs and treatment outcomes.

In the context of benchmarking the energy performance of DWTPs, energy performance has been assessed using several distinct but conceptually different approaches. The most common metric is energy intensity, typically expressed as kilowatt-hours per cubic meter of treated water (kWh/m^3), which provides a simple descriptive indicator but does not account for differences in water quality, treatment requirements, or operating conditions (Rodríguez-Merchan et al. 2021). A second strand of the literature evaluates relative energy efficiency using non-parametric frontier methods such as Data Envelopment Analysis (DEA), where utilities are benchmarked against best-performing peers based on observed inputs and outputs. While DEA has been widely applied due to its flexibility, it is deterministic in nature and attributes all deviations from the frontier to inefficiency, without explicitly accounting for statistical noise or measurement error (Sala-Garrido and Molinos-Senante 2020; Molinos-Senante and Sala-Garrido 2018; Ananda 2019). In contrast, this study adopts a stochastic frontier analysis (SFA) energy-demand framework, in which energy efficiency is defined as the distance from a minimum-energy frontier conditional on output and operating characteristics. This approach allows deviations from the frontier to be decomposed into inefficiency and random noise, providing a statistically grounded measure of energy efficiency. Importantly, efficiency is not constructed as a composite index, but is derived directly from the estimated stochastic energy frontier. However, SFA requires the specification of a functional form for the production/cost frontier, which introduces model structure assumptions (Longo et al. 2023).

Regardless of whether non-parametric (DEA) or parametric (SFA) methods are used to assess the energy efficiency of water facilities, a critical issue is the homogeneity of the decision-making units (DWTPs) being evaluated (De Witte and Marques 2009). Both DEA and SFA are frontier-based methods, meaning that efficiency scores are calculated relative to the best-performing units within the sample. In this context, comparing units with fundamentally different characteristics—such as technology, size, or ownership structure—can lead to biased or misleading results, akin to comparing "apples and pears" (O'Donnell et al. 2008). In the specific context of energy efficiency assessment in DWTPs, only Molinos-Senante and Sala-Garrido (2018) and Molinos-Senante and Maziotis (2025a) have explicitly addressed the issue of unit homogeneity. Both studies adopt the metafrontier approach, which involves partitioning the sample into pre-defined groups based on observable sources of heterogeneity, such as treatment technology or ownership model. Efficiency scores are estimated using group-specific frontiers, while a common metafrontier is used to enable comparisons across groups (Du et al. 2025). However, a major limitation of the metafrontier approach is its reliance on a priori knowledge to define groupings. In many cases, analysts or regulators may lack sufficient information to accurately identify the relevant dimensions of heterogeneity. Moreover, heterogeneity may stem from unobservable or complex factors, such as organizational culture, managerial practices, or local regulatory environments, which cannot be easily captured by observable variables (Maziotis and Molinos-Senante 2025). Moreover, DWTPs are often influenced simultaneously by multiple overlapping sources of heterogeneity, making it difficult to classify them into mutually exclusive groups (Amaral et al. 2025). These challenges highlight the need for alternative approaches—such as latent class models—that allow for data-driven classification and better accommodate unobserved heterogeneity in efficiency analysis (Sun et al. 2025).

This study aims to address the limitations of conventional energy efficiency models that assume homogeneity across facilities by incorporating unobservable sources of heterogeneity into the evaluation of DWTPs using a parametric approach. To illustrate the implications of ignoring such heterogeneity, the results of the proposed method are compared with those obtained from a traditional stochastic frontier model that assumes all DWTPs operate under a common production technology. The case study focuses on a sample of Chilean DWTPs that vary in terms of ownership structure (fully private vs. concessionary utilities), water source, and infrastructure age—factors likely to introduce both observable and unobservable variation in energy performance. To account for this, a latent class stochastic frontier analysis (LCSFA) was employed, which not only offers methodological advantages but also provides practical insights for regulators aiming to design fair, reliable, and context-sensitive performance evaluation frameworks.

The main contribution of this study lies in the assessment of energy efficiency of DWTPs taking into account both observable and unobservable sources of heterogeneity. Unlike previous studies that assume homogeneity or rely on pre-defined groupings, the LCSFA approach adopted in this study allows for data-driven classification of facilities into distinct groups based on their underlying production technologies and operating environments. See more details of previous studies on Table S1. The integration of unobservable heterogeneity in assessing energy efficiency of DWTPs offers not only methodological innovation but also practical value for regulators and utility managers. By comparing the LCSFA results with those obtained from a conventional stochastic frontier model, the study illustrates the risks of misclassification and biased efficiency estimates when heterogeneity is ignored. The findings provide a robust framework for fair and context-sensitive performance benchmarking, enabling more accurate estimation of energy-saving opportunities and better-informed policy design.

2 | Methodology

This section describes the methodology used to estimate the energy efficiency of DWTPs, accounting for the a priori unobservable heterogeneity that characterizes the sector. To address this issue, we employed a LCSFA model. The choice of SFA over non-parametric methods is particularly appropriate in this setting, as DWTP energy consumption data are subject to measurement error, short-term operational shocks, and unobserved heterogeneity. Moreover, the stochastic frontier framework enables explicit testing of how ignoring heterogeneity, by imposing a single pooled frontier, can bias efficiency estimates, which is a central objective of this study (Sala-Garrido and Molinos-Senante 2020). We first introduce the conventional stochastic frontier approach and subsequently explain how this framework is extended to capture differences among DWTPs through a latent class specification.

2.1 | Stochastic Frontier Analysis

SFA is an econometric technique used to estimate the efficiency of decision-making units (water utilities) by separating random noise from inefficiency in the production process (Ben Amor and Mellah 2023). It models deviations from the optimal frontier as a composite error term, combining a symmetric noise component and a one-sided inefficiency term (Murwirapachena et al. 2025). The general form of the stochastic energy frontier is:

$$lnE_i = f(y_i;\alpha) + \varepsilon_i = f(y_i;\alpha) + v_i + u_i \tag{1}$$

where E_i is energy consumption of DWTP i; y_i is the vector of outputs; α is a vector of parameters to be estimated; $v_i \sim N(0,\sigma_v^2)$ is the noise component and; $u_i \sim N^+(0,\sigma_u^2)$ is the inefficiency term, assumed to follow a half-normal distribution (Greene 2004; Orea and Kumbhakar 2004).

This conventional model assumes that all units evaluated operate under a common production technology, which may not hold in practice—particularly in the water sector where treatment technologies vary due to raw water quality, regulatory requirements, and infrastructure conditions (Ananda and Oh 2023).

2.2 | Addressing Heterogeneity: LCSFA

To integrate the heterogeneity of DWTPs in assessing its energy efficiency, the latent class stochastic frontier model proposed by Greene (2004) and Orea and Kumbhakar (2004) is adopted. This model assumes that DWTPs are grouped into unobserved groups or classes, each characterized by a distinct production frontier. The classification is not known a priori but is inferred from the data. Each DWTP is assigned a probability of belonging to each group.

Let us assume there are K DWTPs and J latent groups. The latent group translog frontier for DWTP i in group j is specified as follows (Chang and Tovar 2017):

$$lnE_{i|j} = \alpha_{oj} + \sum_{m=1}^{M}\alpha_{m|j} lny_{mi} + \sum_{n=1}^{N}\alpha_{n|j} lny_{ni} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N}\alpha_{mn|j} lny_{mi} lny_{ni} + \sum_{z=1}^{Z}\omega_{z|j}\xi_{zij} + v_{i|j} + u_{i|j} \tag{2}$$

where E_i denotes annual energy consumption, $y_{m,i}y_{n,i}$ are the quality-adjusted outputs for arsenic and total dissolved solids defined in Equation (15), respectively, and Z_i is a vector of exogenous variables (plant age, water source, and ownership) that are incorporated directly into the stochastic energy frontier as controls affecting conditional energy demand. The terms v_{ij} and u_{ij} represent statistical noise and inefficiency, respectively (Molinos-Senante and Sala-Garrido 2019). Thus, inefficiency is captured exclusively by the one-sided error term u_{ij}, and no separate inefficiency-effects model is specified.

The energy frontier model (Equation (2)) is estimated using maximum likelihood techniques (Greene 2005). The likelihood function of each DWTP i given membership in group j is (Barros 2011):

$$LF_{i|j} = \frac{\varphi\left(\frac{\lambda_j \varepsilon_i|_j}{\sigma_j}\right)}{\Phi(0)} \frac{1}{\sigma_j} \phi\left(\frac{\varepsilon_i|_j}{\sigma_j}\right) \tag{3}$$

where:

$$\varepsilon_i|_j = lnE_i|_j - \alpha_j' y_i \tag{4}$$

$$\sigma_j = \left[\sigma_{uj}^2 + \sigma_{vj}^2\right]^{\frac{1}{2}} \tag{5}$$

$$\lambda_j = \frac{\sigma_{uj}}{\sigma_{vj}} \tag{6}$$

$\varphi(\cdot)$ and $\phi(\cdot)$ are the standard normal density and distribution functions, respectively.

Each DWTP's overall likelihood is a weighted average over all group-specific likelihoods:

$$LF_i = \sum_{j=1}^{J} P_{ij} LF_{i|j}, \quad 0 \le P_{ij} \le 1, \quad \sum_j P_{ij} = 1 \tag{7}$$

where P_{ij} denotes the prior probability that DWTP i belongs to group j (Barros 2009).

The overall likelihood function is derived as follows (Lin and Du 2014):

$$logLF = \sum_{i=1}^{K} logLF_i \tag{8}$$

2.3 | Energy Efficiency Estimation and Posterior Probabilities

Once the model is estimated (Equation (2)), the conditional energy efficiency of DWTP i given group j ($EE_i|_j$) is computed as follows (Lin and Du 2014):

$$EE_i|_j = E\left[\exp\left(-u_i|_j\right) | \varepsilon_i|_j\right] \tag{9}$$

Using Bayes' theorem, the posterior probability of group membership is estimated (Álvarez and del Corral 2010):

$$P(j|i) = \frac{P_{ij} LF_{i|j}}{\sum_{j=1}^{J} P_{ij} LF_{i|j}} \quad (10)$$

The energy efficiency score of DWTP i (EE_i) is calculated as the weighted average across all groups (Lin and Du 2014):

$$EE_i = \sum_{j=1}^{J} \left(P_{j|i} * EE_{i|j} \right) \quad (11)$$

The estimation of energy efficiency allows computing the potential energy savings for each DWTP $\left(PE_i\right)$ as:

$$PE_i = E_i \times \left(1 - EE_i\right) \quad (12)$$

where E_i is the actual energy consumption for the DWTP i expressed in kWh/m^3. It is obtained by dividing total annual electricity consumption (kWh/year) by the annual volume of treated drinking water produced by each DWTP (m^3/year).

2.4 | Group Selection

The optimal number of latent groups is determined using model selection criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBIC) (Maziotis and Molinos-Senante 2025):

$$AIC = -2logLF(j) + 2\mu \quad (13)$$

$$SBIC = -2logLF(j) + log(\pi) * \mu \quad (14)$$

where $logLF$ is the value of the log-likelihood function for group j, μ captures the number of estimated parameters and π is the number of DWTPs to be evaluated (Barros 2009). The preferred model minimizes either criterion (Cullmann and Zloczysti 2014).

3 | Data Sample and Selection

This study analyzes a sample of 146 DWTPs in Chile, which exhibit substantial heterogeneity in both ownership and technical characteristics. All DWTPs included in the analysis operate under the same treatment train configuration (coagulation-flocculation followed by filtration), ensuring technological homogeneity across units. This homogeneity is a fundamental assumption for energy-efficiency benchmarking and allows observed differences in energy consumption to be attributed to variations in operating conditions and pollutant-removal requirements rather than to differences in treatment technology (Ananda and Oh 2023; Molinos-Senante and Maziotis 2025b). From an ownership perspective, the DWTPs are operated by either fully private utilities or concessionary water companies. Although all DWTPs must comply with effluent quality standards established by the Chilean Ministry of Health—aligned with guidelines from the World Health Organization (Muñoz-Arango et al. 2023)—the quality of the raw water they treat varies widely. This variation reflects Chile's diverse geography and regional differences in water availability and source characteristics (DGA 2020).

Because energy efficiency in DWTPs is a synthetic indicator that reflects the energy required to produce drinking water by removing multiple pollutants, we incorporated several input and output variables into its construction. The input variable is the total electricity consumed by each DWTP, measured in kilowatt-hours (kWh) per year. To account for both raw water quality and the production of treated water, and following previous studies (Dong et al. 2017; Sala-Garrido et al. 2025), we defined two quality-adjusted output variables. These variables integrate the concentration of specific pollutants in the influent and effluent, as well as the volume of drinking water produced. The general form of the quality-adjusted output is:

$$Quality\ adjusted\ y_s = V \cdot \left(\frac{P_{sin} - P_{sef}}{P_{sin}} \right) \quad (15)$$

where V is the annual volume of potable water produced (m^3/year), P_{sin} is the concentration of pollutant P_s in the influent (raw water), whereas P_{sef} is the concentration pollutant P_s in the effluent (drinking water). Based on data availability and the primary pollutants typically removed by DWTPs in Chile, we focused on two key substances: (i) arsenic and; (ii) total dissolved solids.

The following example illustrates the estimation of the quality adjusted outputs:

Consider a DWTP producing $V = 5{,}000{,}000\,\mathrm{m}^3$/year of drinking water. Suppose the influent arsenic concentration is $P_{As}^{in} = 0.050$ mg/L and the effluent concentration is $P_{As}^{out} = 0.010$ mg/L. The quality adjusted output for arsenic for the assessed DWTP is: $Quality\ adjusted\ arsenic = 5{,}000{,}000 \times \left(\frac{0.050 - 0.010}{0.050}\right) = \frac{4{,}000{,}000\ \mathrm{m}^3}{\mathrm{year.}}$

Several operational characteristics may influence the energy efficiency of DWTPs (Molinos-Senante and Maziotis 2022; Sowby and Siegal 2024). To control for heterogeneity in operating conditions, we included three exogenous plant characteristics directly in the stochastic energy frontier as determinants of conditional energy consumption. The first is the age of the treatment plant (in years), which may reflect differences in technology or maintenance practices. The second is the type of raw water source, captured by a categorical variable that distinguishes among surface water ($n=45$), groundwater ($n=43$), and mixed sources ($n=58$). The type of raw water source is captured through an ordered categorical variable reflecting increasing treatment complexity and associated energy requirements. Specifically, surface water, groundwater, and mixed sources are coded as increasing values of a single index. This parsimonious representation is adopted to limit parameter proliferation within latent classes and to reflect the benchmarking-oriented focus of the analysis. The resulting coefficient should therefore be interpreted as the marginal effect on conditional energy consumption associated with moving from simpler to more complex source configurations. The third is the ownership type, represented by a binary variable that takes the value 1 for fully private companies ($n=102$) and 0 for concessionary companies ($n=44$) (Sowby and Burian 2018; Yateh et al. 2024).

All data used in this study were provided by the Chilean water regulator, the Superintendencia de Servicios Sanitarios (SISS), for the year 2022, within the scope of its regulatory functions. Due to strict confidentiality requirements, plant-level data cannot be publicly disclosed. However, SISS constitutes an official data source, and the information employed in this analysis has been repeatedly validated by both the regulated utilities and the regulator, ensuring consistency and reliability. Operational, energy consumption, production, and water-quality variables were originally reported at the operational level and were consistently aggregated to annual values for all DWTPs. An exploratory data analysis was conducted to identify potential inconsistencies or extreme values; no relevant outliers were detected, and therefore no observations were excluded or adjusted.

Because no DWTP in the sample exhibits zero influent pollutant concentrations, and because the quality-adjusted outputs defined in Equation (15) remain strictly positive for all observations, the adopted specification does not generate numerical instability or artificial outliers in the estimation of energy efficiency.

Table 1 presents the descriptive statistics for the variables used in the analysis.

4 | Results and Discussion

The latent class stochastic frontier models were estimated using theNlogit/Limdep econometric software. Model estimation was carried out via maximum likelihood methods, following standard practice in stochastic frontier and finite mixture modeling (Lin and Du 2014). Numerical optimization relied on iterative algorithms with convergence assessed using conventional tolerance criteria on the log-likelihood and parameter stability. Multiple sets of starting values were employed to reduce the risk of convergence to local maxima, which is a known issue in latent class and finite-mixture frontier estimation (Greene 2005).

4.1 | Main Attributes of Groups of DWTPs

To determine the optimal number of DWTP groups, we compared AIC and BIC across LCSFA models. The two-class solution minimized both metrics (AIC = 337; BIC = 340) relative to the one-class model (AIC = 358; BIC = 360), while a three-class model failed to converge. We present the groups formed by the latent class model using the posterior probabilities of class membership. Estimated posterior class probabilities indicated a near-even split: 51% of DWTPs ($n = 74$) in Class 1 and 49% ($n = 72$) in Class 2. The main attributes of each class are summarized in Table 2.

Table 2 evidences that Group 1 and Group 2 DWTPs differ notably across several operational and contextual attributes. On average, Group 1 facilities consume more energy annually (183,711 kWh/year) than those in Group 2 (111,173 kWh/year), despite producing a lower volume of treated water (3.74 vs. 5.13 million m^3/year). Group 2 plants also remove higher concentrations of pollutants, particularly arsenic (0.079 mg/L vs. 0.004 mg/L) and total dissolved solids (91.56 mg/L vs. 80.14 mg/L), suggesting differences in raw water quality or treatment intensity. Although Group 2 DWTPs face higher influent arsenic and total dissolved solids concentrations on average, they exhibit higher mean energy efficiency and lower potential energy savings. This result does not reflect lower treatment requirements, but rather lower conditional energy consumption for a given level of quality-adjusted output. In other words, Group 2 DWTPs appear to manage more challenging raw water conditions while operating closer to the minimum-energy frontier. The average plant age is similar between the groups (28.8 years for Group 1 vs. 27.4 years for Group 2). However, there are marked differences in water source and ownership structure. Group 1 has a higher share of plants using mixed sources (48%), while Group 2 has a greater reliance on groundwater (38%) and fewer mixed-source facilities (30%). In terms of ownership, Group 2 is dominated by fully private companies (81%), whereas Group 1 presents a more balanced distribution (59% private, 41% concessionary). These differences confirm that the DWTPs are not a homogeneous group, and thus, benchmarking their energy efficiency should not be conducted jointly without accounting for their underlying heterogeneity.

4.2 | Parameters of the Latent Class Energy Frontier Model

To estimate the energy efficiency of each DWTP and examine how operational and contextual factors shape conditional energy consumption within each group, a latent class stochastic energy frontier model was estimated. As shown in Table 3, the reported coefficients represent the effect of explanatory variables on conditional energy consumption, given the level of quality-adjusted outputs. Energy inefficiency is captured by the one-sided error term and is not directly parameterized as a function of observable covariates. Within a technologically homogeneous treatment framework, the estimated coefficients on quality-adjusted pollutant outputs capture empirical associations between pollutant-removal requirements and conditional energy consumption. These relationships should be interpreted as associative rather than causal, reflecting how energy use varies with pollutant loads under a common treatment technology. Water source is included as an ordered categorical variable representing surface, groundwater, and mixed sources. The reported coefficient reflects the effect on conditional energy consumption of moving along this source gradient.

The results in Table 3 reveal marked differences between Group 1 and Group 2 DWTPs in how pollutant removal requirements and plant characteristics affect energy use. In both groups, the quality-adjusted outputs associated with arsenic and total dissolved solids have statistically significant effects on conditional energy consumption, although the magnitude and functional form of these effects differ. For Group 1, the positive linear coefficients and strongly negative quadratic terms indicate a nonlinear relationship, whereby energy consumption initially increases with higher levels of pollutant removal but at a decreasing rate. The positive and highly significant interaction term between arsenic and total dissolved solids suggests that the simultaneous removal of both pollutants is associated with

TABLE 1 | Descriptive statistics of the Chilean DWTPs evaluated.

Type of variable	Variables	Unit of measurement	Mean	Standard deviation	Minimum	Maximum
Input	Energy consumed	kWh/year	148,049	195,323	1152	1,054,754
Energy saving potential	Volume of water	m^3/year	4,421,294	5,492,996	6641	28,038,677
	Energy consumed	kWh/m^3	0.152	0.224	0.002	0.983
Output	Quality-adjusted arsenic removed	m^3/year	385,700	1,500,167	0.005	8,632,516
	Quality-adjusted total dissolved solids removed	m^3/year	29,058,797	58,454,172	0.010	347,512,697
Environmental variable	Age of plant	Years	28	16	11	72

TABLE 2 | Average of the two identified groups of DWTPs.

Group of DWTPs	Energy consumed (kWh/year)	Volume of water (m^3/year)	Quality-adjusted arsenic removed (m^3/year)	Quality-adjusted total dissolved solids removed (m^3/year)	Age (years)	Source of water	Type of ownership
Group 1	183,711	3,742,747	25,703,582	755,697	28.8	Groundwater: 22% Surface water: 30% Mixed: 48%	Full private: 59% Concessionary: 41%
Group 2	111,173	5,128,511	32,031,227	26,003,800	27.4	Groundwater: 38% Surface water: 32% Mixed: 30%	Full private: 81% Concessionary: 19%

higher energy use, reflecting complementarities in treatment processes. Importantly, the interaction term is not interpreted causally, but as reflecting correlated treatment conditions that are associated with higher energy use for a given level of quality-adjusted output.

A similar nonlinear pattern is observed for Group 2, although the linear coefficients—particularly for arsenic—are substantially larger. This indicates that, for a given increase in quality-adjusted output, energy consumption rises more sharply in Group 2 DWTPs, pointing to differences in treatment intensity, raw water characteristics, or technological configurations across groups.

Plant age also exerts a statistically significant effect on conditional energy consumption in both groups. The negative coefficient implies that, holding output constant, older plants tend to consume less energy, with the magnitude of this effect being considerably larger in Group 2. This result is consistent with Molinos-Senante and Sala-Garrido (2019) and may reflect accumulated operational experience, incremental retrofitting, or the adoption of energy-saving practices over time. The water source variable exhibits opposite effects across groups. In Group 1, moving toward more complex source configurations is associated with higher conditional energy consumption, whereas in Group 2 the coefficient is negative and statistically significant, indicating lower predicted energy use for DWTPs operating under more complex source arrangements. These contrasting effects highlight that the relationship between source characteristics and energy requirements is group-specific and mediated by differences in treatment technology and operating conditions. The positive and statistically significant ownership coefficient indicates that, holding output constant, DWTPs operated by fully private companies exhibit higher conditional energy consumption than concessionary utilities. However, this does not imply lower energy efficiency, as efficiency is determined by deviations from the frontier rather than by the frontier position itself. Moreover, this association should not be interpreted causally. In the cross-sectional setting considered here, ownership may proxy for unobserved factors such as regional operating conditions, historical investment patterns, or institutional arrangements that are not explicitly modeled. As such, the estimated ownership coefficient captures an empirical association rather than a direct governance or managerial effect.

Finally, the estimated sigma and lambda parameters confirm the presence of statistically significant inefficiency and support the existence of distinct latent classes with heterogeneous energy consumption frontiers. Together, these results underscore the

TABLE 3 | Estimates of the latent class stochastic energy frontier.

	Group 1				Group 2				Single group			
Variables	**Coeff.**	**St. Err.**	**T-stat**	***p***	**Coeff.**	**St. Err.**	**T-stat**	***p***	**Coeff.**	**St. Err.**	**T-stat**	***p***
Constant	1.563	0.064	**24.452**	0.000	0.146	0.096	1.511	0.131	−0.459	0.678	−0.676	0.499
Arsenic	0.184	0.059	**3.141**	0.002	0.972	0.050	**19.438**	0.000	0.428	0.156	**2.740**	0.006
Total dissolved solids	0.186	0.065	**2.851**	0.004	0.232	0.047	**4.974**	0.000	0.100	0.146	0.681	0.496
Arsenic^2	−0.876	0.027	**−32.249**	0.000	0.369	0.120	**3.069**	0.002	0.233	0.082	**2.853**	0.004
Total dissolved solids^2	−0.562	0.017	**−33.641**	0.000	−0.613	0.158	**−3.878**	0.000	0.145	0.181	0.804	0.421
Arsenic*total dissolved solids	0.565	0.014	**39.530**	0.000	0.330	0.140	**2.359**	0.018	−0.201	0.171	−1.171	0.242
Age	−0.008	0.001	**−9.664**	0.000	−0.045	0.003	**−17.700**	0.000	−0.007	0.006	−1.077	0.281
Water source	−0.172	0.032	**−5.408**	0.000	0.129	0.059	**2.197**	0.028	0.236	0.121	***1.948***	0.051
Ownership	0.775	0.018	**42.044**	0.000	0.760	0.100	**7.623**	0.000	0.417	0.215	***1.938***	0.053
Sigma	1.078	0.102	**10.557**	0.000	0.604	0.071	**8.488**	0.000	3.215	0.542	**5.929**	0.000
Lambda	3.309	0.347	**9.531**	0.000	3.917	0.454	**8.622**	0.000	0.972	0.171	**5.686**	0.000
Estimated prior probabilities for each class membership												
Group 1	0.577	0.049	**11.696**	0.000								
Group 2	0.423	0.049	**8.571**	0.000								
Log-likelihood	−150.8								210.09			

Note: Bold indicates that coefficients are statistically significant at 5% significance level. Bold italic indicates that coefficients are statistically significant at 10% significance level. Quality-adjusted outputs for arsenic and total dissolved and energy consumption are expressed in logarithms.

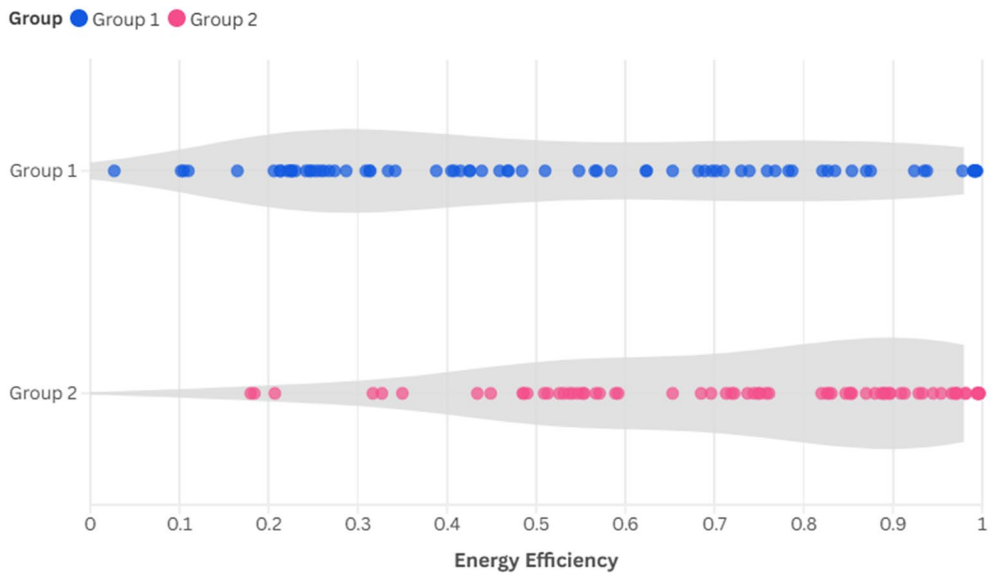

FIGURE 1 | Energy efficiency scores for each group of DWTPs.

importance of accounting for heterogeneity when benchmarking DWTP energy performance, as the same operational or contextual factor may influence energy use differently across groups.

Overall, these results underscore the importance of accounting for underlying heterogeneity when evaluating DWTP performance. Group-specific drivers imply that a one-size-fits-all benchmarking approach would be misleading, potentially masking key structural and operational differences. Tailored efficiency improvement strategies—considering pollutant profiles, infrastructure age, and ownership models—are essential for effective energy management in the sector.

For comparison purposes, we estimated a traditional SF model by assuming a common frontier for all DWTPs. The estimated results are also shown in Table 3. When the entire sample of DWTPs is modeled as a single, homogeneous group, the estimated coefficients show weaker statistical significance and reduced explanatory power compared to the independent latent class models. Several variables that were highly significant in the group-specific models—such as arsenic, total dissolved solids, and plant age—lose significance in the pooled model, indicating that key efficiency drivers are obscured when group-level heterogeneity is not accounted for. For example, the coefficient for arsenic removal is positive but not statistically significant ($p = 0.496$), and the quadratic terms and interaction effects, which captured nonlinearities and synergies in the class-based models, are largely diluted. Moreover, ownership and water source variables are only marginally significant ($p \approx 0.05$), in contrast to their strong and opposing effects across groups in the segmented analysis. These results suggest that pooling the DWTPs into a single group leads to biased or attenuated estimates, masking important structural and operational differences.

4.3 | Energy Efficiency Estimations

The estimated latent class energy stochastic frontier models were used to compute the energy efficiency score of each individual assessed DWTP. Figure 1 displays the distribution of energy efficiency scores for DWTPs in Groups 1 and 2. These estimates should be interpreted as conditional on the maintained distributional assumptions of the stochastic frontier model. Notable differences are observed in both the average performance and the dispersion of efficiency scores between the two groups. Group 1 exhibits a wide range of energy efficiency values, from as low as 0.027 to nearly full efficiency (0.994), with scores distributed relatively evenly across the entire range. This is reflected in a lower average efficiency of 0.534 and a higher standard deviation of 0.286, suggesting substantial variability in operational performance within the group. In contrast, Group 2 demonstrates a more concentrated distribution of efficiency scores, skewed toward the upper end of the scale. The average efficiency in this group is significantly higher, at 0.737, with a lower standard deviation of 0.227 and a narrower range (0.180–0.997), indicating greater homogeneity and overall better energy performance.

These differences highlight the importance of accounting for heterogeneity when evaluating the energy efficiency of DWTPs. Group 2 plants not only achieve higher average efficiency levels but also operate within a more uniform performance band, suggesting that they may share common structural or operational characteristics conducive to energy-efficient operation. In contrast, the broad spread of efficiency scores in Group 1 points to a mix of high- and low-performing plants, likely influenced by diverse technological configurations, raw water quality, and management practices.

The results of our study are broadly consistent with the only other known analysis of DWTP energy efficiency using a SFA approach. For the 146 DWTPs evaluated in our study, the average estimated energy efficiency score was 0.634, whereas Molinos-Senante and Maziotis (2025a), Molinos-Senante and Maziotis (2025b) reported a lower average of 0.465 for a smaller sample of 96 Chilean DWTPs. In contrast, most previous studies have employed non-parametric methods, such as DEA, which tend to produce lower average efficiency scores. For example, studies of Chilean DWTPs reported mean energy efficiency scores of 0.28 (Molinos-Senante and Sala-Garrido 2019), 0.329 (Maziotis et al. 2023), and 0.408 (Molinos-Senante and Sala-Garrido 2018). When considering facilities outside of Chile, estimated average energy efficiency scores tend to be somewhat higher. For instance, Amaral et al. (2025) reported a mean score of 0.569 for water utilities in Portugal, while Ananda (2019) found an average of 0.683 for Australian ones. It is important to note, however, that beyond methodological differences, a range of contextual and operational factors—including water source, plant age, ownership structure, and the type of pollutants removed—can also influence energy efficiency outcomes (Amaral et al. 2025). Therefore, comparisons across studies and countries should be interpreted with caution, particularly when samples differ significantly in terms of technological, environmental, or regulatory conditions.

To evaluate the impact of not accounting for heterogeneity in energy efficiency estimation, Figures 2 and 3 compare the energy efficiency scores obtained from the LCSFA with those estimated using a single, pooled frontier. Figure 2 presents the results for DWTPs in Group 1, while Figure 3 shows the corresponding comparison for Group 2. In both groups, the differences between the two estimation methods are substantial. For Group 1 (Figure 2), the average energy efficiency score estimated using the LCSFA model is 0.534, compared to 0.762 under the common frontier approach. Notably, in 54 out of 74 DWTPs (73%) in this group, the efficiency scores derived from the LCSFA model are lower than those estimated using the pooled frontier. In several cases, LCSFA identifies DWTPs with efficiency scores below 0.1, which are rated above 0.7 by the common frontier, highlighting a significant distortion. In contrast, for Group 2 (Figure 3), the trend is reversed. The average efficiency score under the LCSFA model is 0.737,

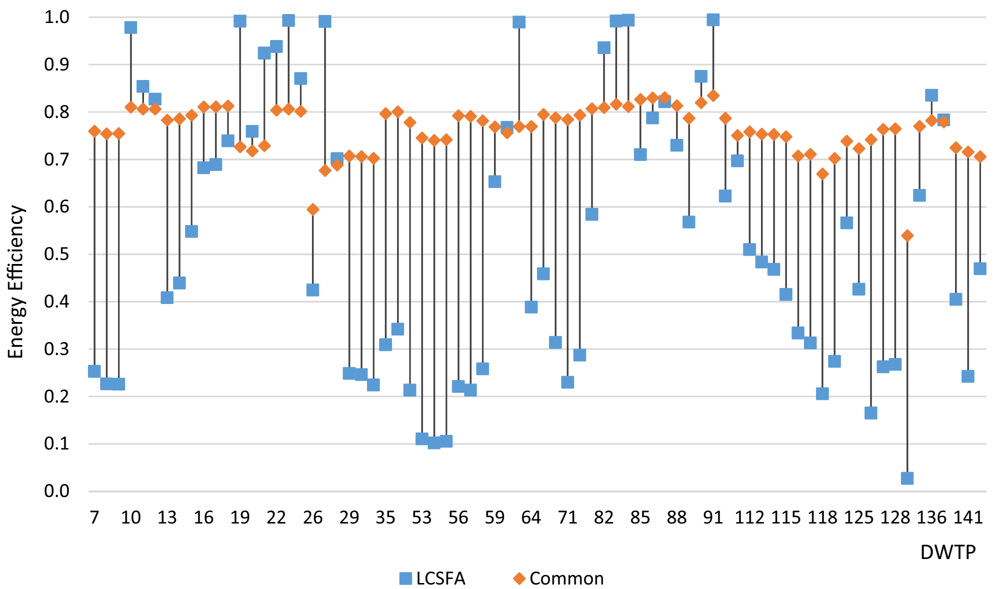

FIGURE 2 | Comparison of energy efficiency scores estimated under latent class stochastic frontier analysis (LCSFA) and assuming a common frontier for Group 1.

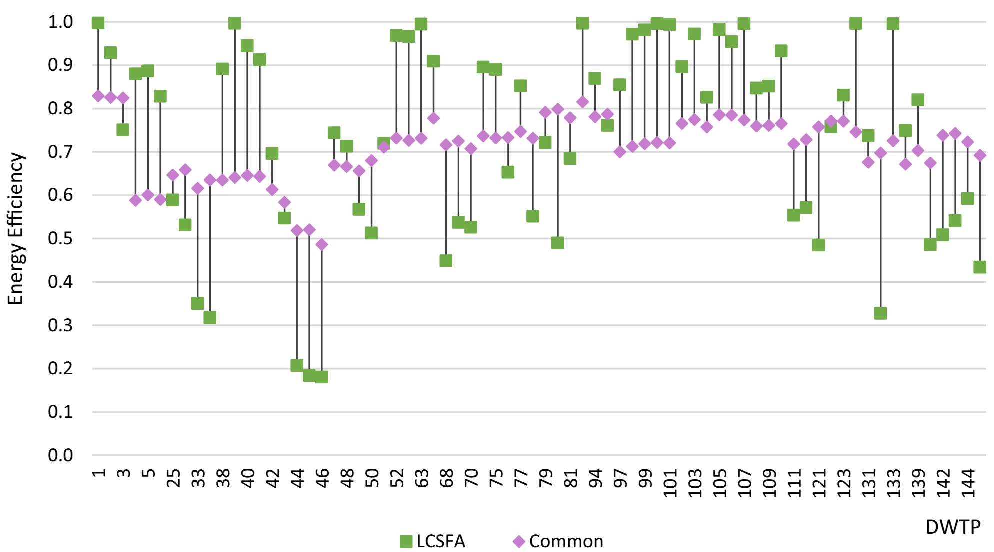

FIGURE 3 | Comparison of energy efficiency scores estimated under latent class stochastic frontier analysis (LCSFA) and assuming a common frontier for Group 1.

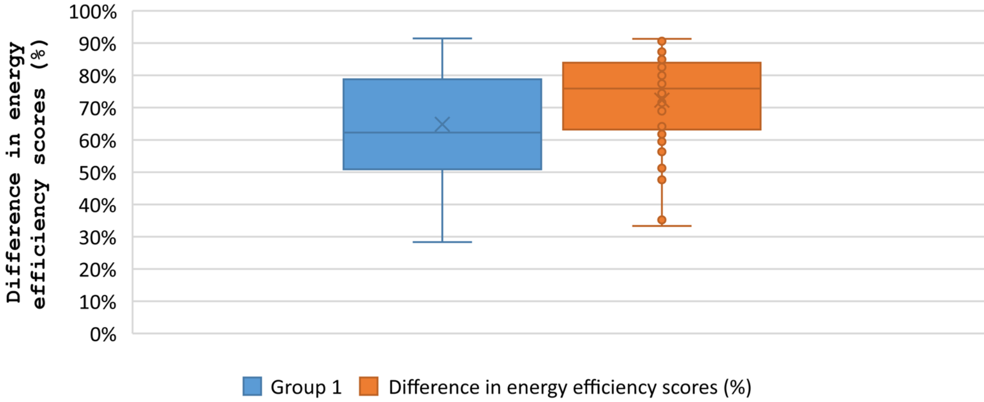

FIGURE 4 | Difference in energy efficiency scores estimated under latent class stochastic frontier analysis (LCSFA) and assuming a common frontier.

slightly higher than the 0.709 estimated using the pooled frontier. In this case, 42 out of 72 DWTPs (58%) show higher efficiency scores under LCSFA, suggesting that the common frontier tends to underestimate the performance of many plants in this group.

Figure 4 illustrates the distribution of differences in energy efficiency scores between the LCSFA and the pooled frontier specification, separately for Group 1 and Group 2 DWTPs. It shows that efficiency differences are substantial in both groups, but their distribution differs markedly. For Group 1, differences are widely dispersed, with a median difference of approximately 60%–65% and a broad interquartile range, indicating that pooled frontier estimates tend to assign noticeably higher efficiency scores relative to the latent class model for a large share of DWTPs in this group. The long lower tail suggests that, for some plants, the divergence between the two modeling approaches is particularly pronounced. In contrast, Group 2 exhibits a more concentrated distribution of efficiency differences, with a higher median (around 75%) and a narrower interquartile range. This indicates that, while efficiency estimates under the two models also differ systematically for Group 2 DWTPs, the magnitude of these differences is generally more homogeneous across plants. In both groups, the efficiency estimates obtained from the common frontier are more compressed and tend to cluster around moderate values. These findings underscore the importance of adopting segmented frontier models, such as LCSFA, which explicitly account for unobserved heterogeneity across groups. To complement the frontier coefficient analysis, we also examine how plant characteristics are reflected in the estimated energy efficiency scores. Average efficiency levels differ systematically across ownership types and plant age categories, indicating that while some characteristics shift the conditional energy frontier, their net effect on efficiency depends on how closely DWTPs operate relative to that frontier. This confirms that frontier coefficients and efficiency outcomes should not be interpreted interchangeably.

The differences in energy efficiency scores estimated under LCSFA and common frontier approaches have important implications for performance benchmarking and regulatory decision-making in the water sector. Applying a single, pooled efficiency frontier across all DWTPs can lead to biased and misleading assessments, particularly for utilities operating under distinct technical or environmental conditions. This not only undermines the credibility of benchmarking exercises but may also result in inequitable policy interventions, such as misaligned incentives or investment priorities. In contrast, adopting a latent class approach enables regulators and utility managers to tailor performance evaluations and improvement strategies to the specific characteristics of each group of plants.

In the context of water utility benchmarking, ranking utilities based on their performance is critical for several interrelated reasons, particularly those linked to operational efficiency, financial sustainability, public accountability, and strategic planning (Berg 2020; Sakai 2024). Moreover, in some countries and regions, such as Colombia, England and Wales, and Italy, these performance rankings are directly used as inputs for setting water tariffs (Wareg 2019). In our study, Figures 5 and 6 illustrate how the ranking of the top 10 and bottom 10 DWTPs changes depending on whether energy efficiency is estimated using the LCSFA or a common frontier, for Group 1 and Group 2, respectively. The complete ranking for the 146 assessed DWTPs is shown in Tables S1 and S2. These ranking results are intended to illustrate systematic differences between modeling approaches rather than to provide definitive regulatory rankings for individual DWTPs and should therefore be interpreted as indicative rather than deterministic.

For Group 1 (Figure 5), while the DWTPs ranked first and last remain the same under both estimation methods, the rankings of the remaining plants change significantly. This demonstrates how failing to account for heterogeneity in performance assessment can result in substantial misclassification, with potentially serious implications if rankings are linked to incentives or regulatory decisions. A similar pattern is observed for Group 2 (Figure 6), where the first and last-ranked DWTPs are consistent across both methods, but the intermediate rankings vary depending on the model used. These results reinforce the importance of using heterogeneity-aware methods like LCSFA when rankings are used for decision-making, as overlooking structural and operational differences among DWTPs can lead to misinformed performance evaluations and unfair regulatory outcomes.

4.4 | Potential Energy Savings

The estimation of the energy efficiency scores at DWTP level allows estimating potential energy savings if they were efficient (Figure 7). The results clearly show that Group 1 DWTPs

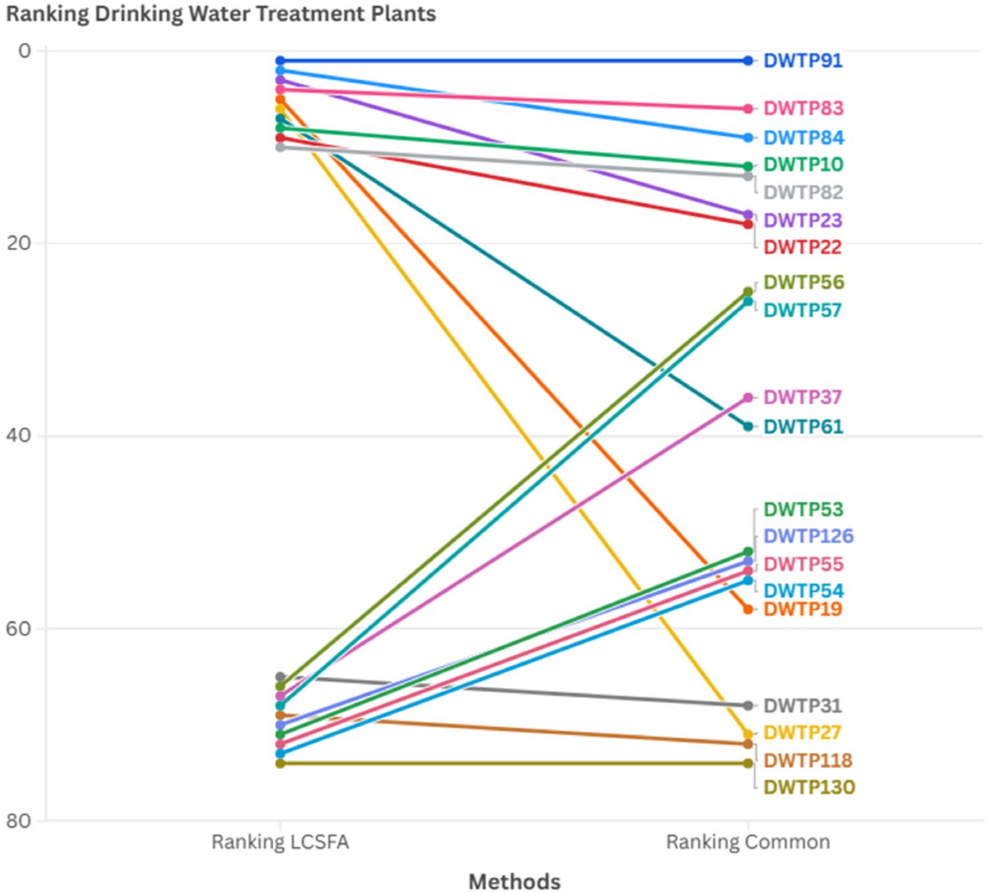

FIGURE 5 | Ranking of the top 10 and bottom 10 energy efficient DWTPs within Group 1.

exhibit a wider range and higher potential for energy savings. With an average value of 0.112 kWh/m^3, potential energy savings in this group range from near zero up to approximately 0.43 kWh/m^3, indicating significant room for improvement in many facilities. The density of points across the range further suggests that energy inefficiency is more variable and widespread within Group 1. This aligns with earlier findings showing lower average energy efficiency and higher dispersion in this group. By contrast, Group 2 DWTPs display lower and more concentrated potential energy savings, with most values below 0.05 kWh/m^3. The estimated average energy saving is 0.044 kWh/m^3. Moreover, only a few outliers in Group 2 show potential savings above 0.2 kWh/m^3. This reflects the group's generally higher energy efficiency and greater operational consistency, as previously observed.

Results on Figure 7 underscore the importance of targeting energy efficiency interventions primarily at DWTPs in Group 1, where the greatest energy reduction potential lies. Tailored strategies in these plants could deliver meaningful reductions in energy consumption and associated operational costs, while Group 2 plants may benefit more from fine-tuning or maintaining best practices rather than large-scale retrofits.

4.5 | Main Policy Implications

The findings of this study involve relevant implications for the design and implementation of energy efficiency policies, performance benchmarking frameworks, and regulatory practices in the drinking water sector. A central policy implication concerns the use of group-specific benchmarking rather than a single, pooled frontier. Our results clearly show that treating all DWTPs as a single group, as done in conventional frontier models, leads to biased efficiency estimates. This has direct consequences for regulatory benchmarking, especially in countries or regions where efficiency metrics are linked to tariff-setting or performance-based incentives. Therefore, integrating heterogeneity-aware methods like LCSFA into regulatory benchmarking frameworks is essential to avoid misclassification and ensure equity in how utilities are evaluated and rewarded.

Furthermore, the identification of group-specific inefficiency drivers supports the case for targeted energy efficiency interventions. In our case study, Group 1 DWTPs should be prioritized in national or regional energy reduction strategies, particularly in programs supported by climate finance, public subsidies, or performance improvement contracts. Investments in upgrading treatment technologies, retrofitting outdated equipment, and operator training would likely yield the highest returns in these facilities. In contrast, Group 2 DWTPs present a different energy efficiency pattern, suggesting that interventions should focus on optimization rather than large-scale capital investment. For these plants, performance improvements could be pursued through enhanced operational practices, fine-tuning chemical dosing strategies, or digital monitoring systems that reduce energy waste.

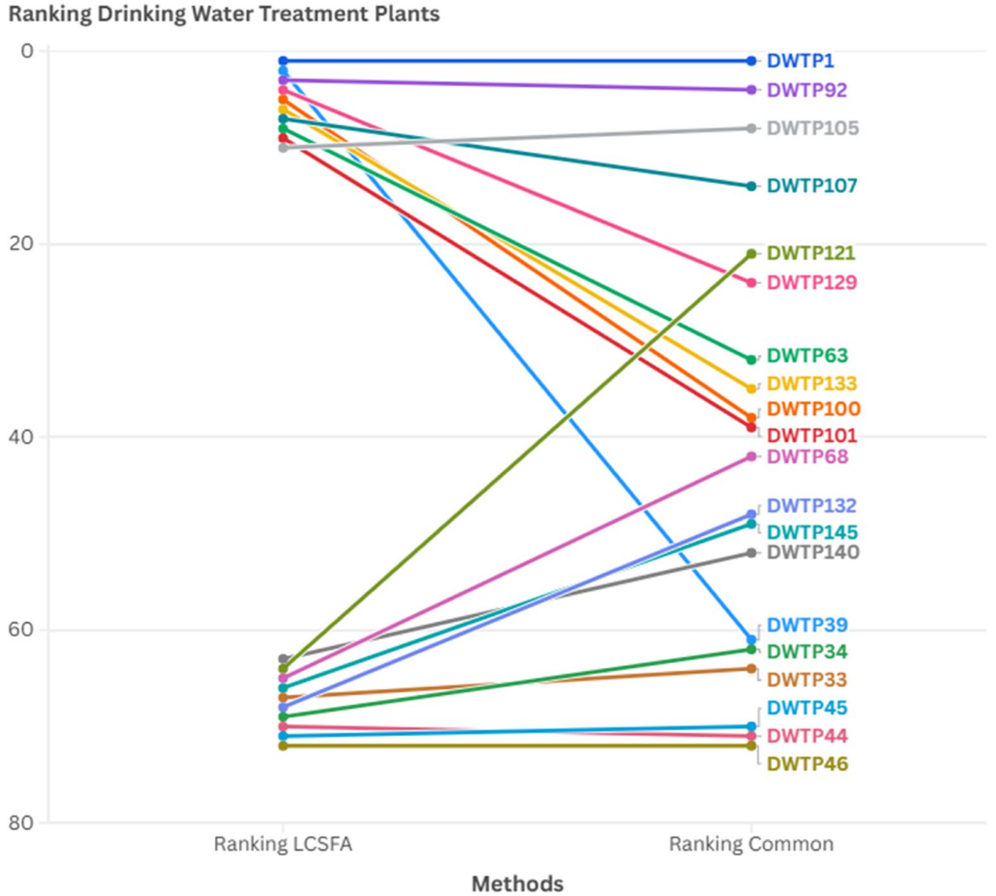

FIGURE 6 | Ranking of the top 10 and bottom 10 energy efficient DWTPs within Group 2.

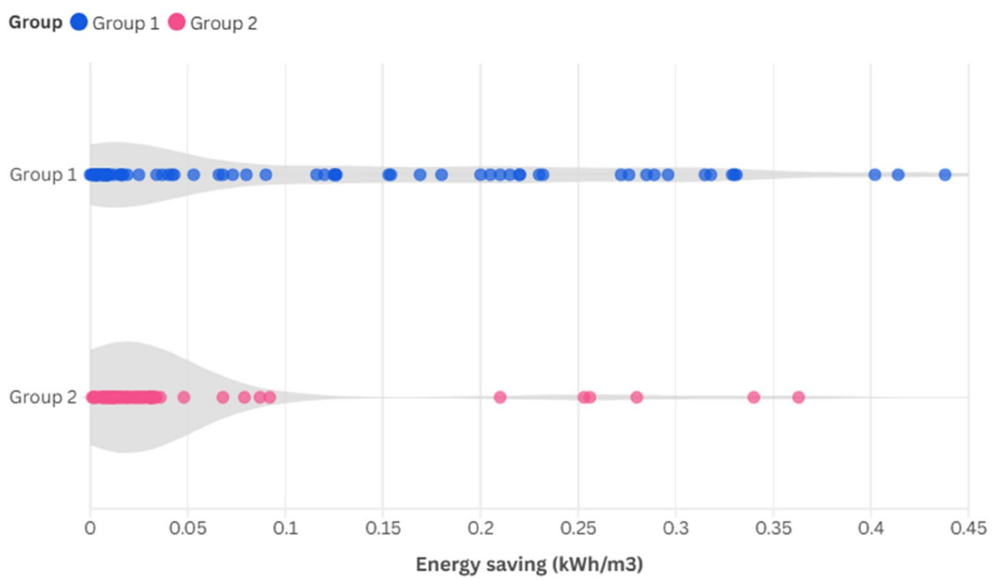

FIGURE 7 | Potential energy savings whether DWTPs were efficient.

Differences associated with ownership structure should be interpreted with caution. Although ownership is statistically associated with variations in conditional energy consumption, the cross-sectional nature of the analysis does not allow disentangling ownership effects from other correlated factors, such as regional operating conditions, historical investment cycles, or unobserved institutional characteristics. As a result, these findings should not be interpreted as evidence of superior or inferior governance performance, nor as a basis for performance-linked incentives or penalties. Instead, the observed association between ownership type and energy use should be viewed as a hypothesis-generating result that highlights the relevance of institutional arrangements for energy performance in drinking water treatment.

5 | Conclusions

Assessing the energy efficiency of DWTPs is gaining increasing attention in the context of transitioning toward an energy-neutral urban water cycle. However, to obtain unbiased and reliable energy efficiency estimates that can effectively inform policymaking and managerial decisions, it is essential to account for both observable and unobservable heterogeneity among the facilities being evaluated. This study contributes to the growing literature on DWTP energy efficiency by introducing a LCSFA approach, which explicitly incorporates these sources of heterogeneity. Applying the LCSFA model to a representative sample of 146 DWTPs in Chile, two distinct latent groups were identified with significantly different efficiency profiles, operational characteristics, and energy performance drivers.

Ignoring unobserved heterogeneity can lead to systematically different efficiency estimates relative to heterogeneity-aware models, with potential implications for benchmarking and performance comparison. When DWTPs were assessed under a single, pooled frontier, energy efficiency scores were systematically larger in Group 1 and lower in Group 2. This misrepresentation was particularly evident in the ranking of facilities. For example, some DWTPs that ranked among the most efficient under the latent class model dropped dramatically in the rankings when evaluated under the pooled model. Such discrepancies highlight the policy risks associated with homogeneous benchmarking, especially in contexts where rankings are used to inform tariffs, investment decisions, or regulatory oversight.

Group-specific estimation results revealed that arsenic and total dissolved solids are key variables influencing energy consumption in both groups, though the nature and intensity of their effects differ. Group 1 of DWTPs showed nonlinear relationships, with diminishing returns in pollutant removal and a significant interaction effect between arsenic and TDS. Group 2 of DWTPs, on the other hand, exhibited stronger linear relationships, particularly for arsenic removal, suggesting a different treatment regime or raw water challenge. These findings underscore the need for context-aware performance evaluations that account for the specific pollutant loads and treatment objectives faced by each plant.

The role of exogenous variables also varied between groups. Plant age was negatively associated with energy efficiency in both cases, though its impact was much more pronounced in Group 2, possibly reflecting differences in technological upgrades or maintenance practices. Water source had opposite effects across groups, while ownership structure—with fully private utilities outperforming concessionary ones—was consistently significant. These results offer practical insights for utility managers and regulators: energy efficiency improvement strategies must be tailored to plant-specific characteristics and operating conditions. Group-level analysis enables more targeted interventions, resource allocation, and policy design.

From a methodological standpoint, this study demonstrates that LCSFA is a powerful tool for performance assessment in infrastructure sectors characterized by technological and operational diversity. It enables the estimation of class-specific frontiers without requiring prior knowledge of group membership, thus overcoming one of the key limitations of metafrontier models. The approach is particularly relevant for those countries where water utilities operate under different ownership regimes, serve diverse geographic regions, and face varying environmental and regulatory constraints. Future research could expand on these findings by incorporating time-series data to evaluate dynamic efficiency changes or by linking efficiency outcomes to tariff structures and environmental indicators.

A limitation of this study is that uncertainty around energy efficiency estimates and rank positions is not explicitly quantified. While stochastic frontier analysis inherently distinguishes inefficiency from statistical noise, the present analysis focuses on point estimates to highlight systematic biases arising from ignoring unobserved heterogeneity. Formal uncertainty assessment would be required if efficiency scores or rankings were to be used directly for regulatory purposes such as tariff setting or performance-based incentives. A further limitation is that efficiency and savings estimates are conditional on the assumed inefficiency distribution (half-normal). Alternative distributional assumptions (e.g., truncated-normal or exponential) may yield different efficiency levels and potentially affect latent-class assignment in finite mixture frontier models. While the study's main objective is to compare pooled versus heterogeneity-aware benchmarking under a consistent baseline specification, future research should formally test robustness to alternative inefficiency distributions to quantify model risk. Addressing these limitations represents an important avenue for future research, particularly in applications where efficiency benchmarking feeds directly into policy or regulatory decisions.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

References

Álvarez, A., and J. del Corral. 2010. "Identifying Different Technologies Using a Latent Class Model: Extensive vs. Intensive Dairy Farms." *European Review of Agricultural Economics* 37: 231–250.

Amaral, A. L., R. Martins, and L. C. Dias. 2025. "Drivers of Energy Efficiency in the Portuguese Water Industry." *Environment, Development and Sustainability*. In Press.

Ananda, J. 2019. "Explaining the Environmental Efficiency of Drinking Water and Wastewater Utilities." *Sustainable Production and Consumption* 17: 188–195.

Ananda, J., and D. Oh. 2023. "Assessing Environmentally Sensitive Productivity Growth: Incorporating Externalities and Heterogeneity Into Water Sector Evaluations." *Journal of Productivity Analysis* 59, no. 1: 45–60.

Barros, C. P. 2009. "The Measurement of Efficiency of UK Airports, Using a Stochastic Latent Class Frontier Model." *Transport Reviews* 29, no. 4: 479–498.

Barros, C. P. 2011. "Cost Efficiency of African Airports Using a Finite Mixture Model." *Transport Policy* 18: 807–813.

Ben Amor, T., and T. Mellah. 2023. "Cost Efficiency of Tunisian Water Utility Districts: Does Heterogeneity Matter?" *Utilities Policy* 84: 101616.

Berg, S. 2020. "Performance Assessment Using Key Performance Indicators (KPIs) for Water Utilities: A Primer." *Water Economics and Policy* 6, no. 2: 2050001.

Bukhary, S., J. Batista, and S. Ahmad. 2020. "Water-Energy-Carbon Nexus Approach for Sustainable Large-Scale Drinking Water Treatment Operation." *Journal of Hydrology* 587: 124953.

Chang, V., and B. Tovar. 2017. "Heterogeneity Unobserved and Efficiency: A Latent Class Model for West Coast of South Pacific Port Terminals." *Journal of Transport Economics and Policy* 51, no. 2: 139–156.

Chini, C. M., and A. S. Stillwell. 2018. "The State of U.S. Urban Water: Data and the Energy-Water Nexus." *Water Resources Research* 54, no. 3: 1796–1811.

Cullmann, A., and P. Zloczysti. 2014. "R&D Efficiency and Heterogeneity – A Latent Class Application for the OECD." *Applied Economics* 46, no. 30: 3750–3762.

De Witte, K., and R. C. Marques. 2009. "Capturing the Environment, a Metafrontier Approach to the Drinking Water Sector." *International Transactions in Operational Research* 16, no. 2: 257–271.

DGA. 2020. Atlas de Calidad del Agua en Chile. http://snia.dga.cl/transparencia/documentos/aguas_atlas_19022021_dsm.pdf.

Dong, X., X. Zhang, and S. Zeng. 2017. "Measuring and Explaining Eco-Efficiencies of Wastewater Treatment Plants in China: An Uncertainty Analysis Perspective." *Water Research* 112: 195–207.

Du, M., B. Wang, Z. Chen, and L. Liao. 2025. "Productivity Evaluation of Urban Water Supply Industry in China: A Metafrontier-Biennial Cost Malmquist Productivity Index Approach." *Annals of Operations Research* 355: 2351–2371.

Greene, W. H. 2004. "Interpreting Estimated Parameters and Measuring Individual Heterogeneity in Random Coefficient Models", Working Paper, Stern School of Business, New York University, New York.

Greene, W. H. 2005. "Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model." *Journal of Econometrics* 126: 269–303.

Lam, K. L., S. J. Kenway, and P. A. Lant. 2017. "Energy Use for Water Provision in Cities." *Journal of Cleaner Production* 143: 699–709.

Lin, B., and K. Du. 2014. "Measuring Energy Efficiency Under Heterogeneous Technologies Using a Latent Class Stochastic Frontier Approach: An Application to Chinese Energy Economy." *Energy* 76: 884–890.

Longo, S., A. Hospido, and M. Mauricio-Iglesias. 2023. "Energy Efficiency in Wastewater Treatment Plants: A Framework for Benchmarking Method Selection and Application." *Journal of Environmental Management* 344: 118624.

Maziotis, A., M. Mocholi-Arce, R. Sala-Garrido, and M. Molinos-Senante. 2023. "Energy Efficiency of Drinking Water Treatment Plants: A Methodological Approach for Its Ranking." *Science of the Total Environment* 862: 160840.

Maziotis, A., and M. Molinos-Senante. 2025. "Benchmarking Technical Efficiency of Water Utilities in Chile Under Heterogeneity: A Latent Class Frontier Approach." *Utilities Policy* 97: 102076.

Molinos-Senante, M., and C. Guzmán. 2018. "Benchmarking Energy Efficiency in Drinking Water Treatment Plants: Quantification of Potential Savings." *Journal of Cleaner Production* 176: 417–425.

Molinos-Senante, M., and A. Maziotis. 2022. "Influence of Environmental Variables on the Energy Efficiency of Drinking Water Treatment Plants." *Science of the Total Environment* 833: 155246.

Molinos-Senante, M., and A. Maziotis. 2025a. "Energy Efficiency Assessment of Drinking Water Treatment Plants Incorporating Technological Differences and Exogenous Variables." *Energy Nexus* 19: 100470.

Molinos-Senante, M., and A. Maziotis. 2025b. "The Influence of Environmental Variables on the Carbon Performance of Water Companies Across Time." *Sustainable Development* 33, no. 3: 4718–4731.

Molinos-Senante, M., and R. Sala-Garrido. 2018. "Evaluation of Energy Performance of Drinking Water Treatment Plants: Use of Energy Intensity and Energy Efficiency Metrics." *Applied Energy* 229: 1095–1102.

Molinos-Senante, M., and R. Sala-Garrido. 2019. "Assessment of Energy Efficiency and Its Determinants for Drinking Water Treatment Plants Using A Double-Bootstrap Approach." *Energies* 12: 765.

Muñoz-Arango, D., F. Torres-Rojas, N. Tapia, R. Nerenberg, and I. T. Vargas. 2023. "Perchlorate and Chlorate Assessment in Drinking Water in Northern Chilean Cities." *Environmental Research* 233: 116450.

Murwirapachena, G., J. Dikgang, and R. Mulwa. 2025. "Benchmarking South African Water Utilities Using Three Efficiency Analysis Methods." *Applied Economics* 57, no. 31: 4472–4485.

Nault, J., and F. Papa. 2015. "Lifecycle Assessment of a Water Distribution System Pump." *Journal of Water Resources Planning and Management* 141, no. 12: A4015004.

O'Donnell, C. J., D. S. P. Rao, and G. E. Battese. 2008. "Metafrontier Frameworks for the Study of Firm-Level Efficiencies and Technology Ratios. Metafrontier Frameworks for the Study of Firm-Level Efficiencies and Technology Ratios." *Empirical Economics* 34, no. 2: 231–255.

Orea, L., and S. C. Kumbhakar. 2004. "Efficiency Measurement Using a Latent Class Stochastic Frontier Model." *Empirical Economics* 29: 169–183.

Rodríguez-Merchan, V., C. Ulloa-Tesser, C. Baeza, and Y. Casas-Ledón. 2021. "Evaluation of the Water–Energy Nexus in the Treatment of Urban Drinking Water in Chile Through Exergy and Environmental Indicators." *Journal of Cleaner Production* 317: 128494.

Sakai, H. 2024. "Review of Research on Performance Indicators for Water Utilities." *Aqua—Water Infrastructure, Ecosystems and Society* 73, no. 2: 167–182.

Sala-Garrido, R., A. Maziotis, and M. Molinos-Senante. 2025. "Assessing Eco-Efficiency of Drinking Water Treatment Plants: A Synthetic Index Approach Within Water-Energy-Carbon Nexus." *Journal of Cleaner Production* 495: 145067.

Sala-Garrido, R., and M. Molinos-Senante. 2020. "Benchmarking Energy Efficiency of Water Treatment Plants: Effects of Data Variability." *Science of the Total Environment* 701: 134960.

Santana, M. V. E., Q. Zhang, and J. R. Mihelcic. 2014. "Influence of Water Quality on the Embodied Energy of Drinking Water Treatment." *Environmental Science & Technology* 48, no. 5: 3084–3091.

Smith, K., S. Liu, and T. Chang. 2016. "Contribution of Urban Water Supply to Greenhouse Gas Emissions in China." *Journal of Industrial Ecology* 20, no. 4: 792–802.

Sowby, R. B. 2023. "Making Waves: Research to Support Water and Wastewater Utilities in the Transition to a Clean-Energy Future." *Water Research* 233: 119739.

Sowby, R. B., and S. J. Burian. 2018. "Statistical Model and Benchmarking Procedure for Energy Use by US Public Water Systems." *Journal of Sustainable Water in the Built Environment* 4, no. 4: 04018010.

Sowby, R. B., and A. Capener. 2022. "Reducing Carbon Emissions Through Water Conservation: An Analysis of 10 Major U.S. Cities." *Energy Nexus* 7: 100094.

Sowby, R. B., and A. C. Siegal. 2024. "The Increasing Energy Intensity of Drinking Water Supply." *Energy Reports* 11: 6233–6237.

Sun, H., B. K. Edziah, L. Li, C. Jiang, and Z. Li. 2025. "Assessing Persistent and Transient Energy Efficiency Performances Across

Heterogeneous Technologies: A Global Analysis." *Environmental Impact Assessment Review* 115: 107983.

United Nations. 2010. The Human Right to Water and Sanitation: Resolution. https://digitallibrary.un.org/record/687002?v=pdf&ln=es.

United Nations. 2015. Sustainable Development Goals. https://sustainabledevelopment.un.org/?menu=1300.

Wareg. 2019. Sustainable Tariff: A Bridge Between Citizens, Utilities and Regulators. https://www.wareg.org/documents/sustainable-tariff-a-bridge-between-citizens-utilities-and-regulators/.

Yateh, M., F. Li, Y. Tang, C. Li, and B. Xu. 2024. "Energy Consumption and Carbon Emissions Management in Drinking Water Treatment Plants: A Systematic Review." *Journal of Cleaner Production* 437: 140688.

Zhang, Q., J. Nakatani, T. Wang, C. Chai, and Y. Moriguchi. 2017. "Hidden Greenhouse Gas Eemissions for Water Utilities in China's Cities." *Journal of Cleaner Production* 162: 665–677. https://doi.org/10.1016/j.jclepro.2017.06.042.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Comparison of previous studies assessing energy efficiency of DWTPs. **Table S2:** Ranking of Group 1 DWTPs according to its energy efficiency estimation. **Table S3:** Ranking of Group 2 DWTPs according to its energy efficiency estimation.