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Assessing eco-efficiency of drinking water treatment plants: A synthetic index approach within water-energy-carbon nexus

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A R T I C L E I N F O

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A B S T R A C T

Drinking water treatment plants (DWTPs) are essential facilities significantly contributing to greenhouse gas (GHG) emissions and operational costs within the provision of drinking water services. Unlike previous studies that evaluated the performance of DWTPs based on a single criterion, this study introduces a synthetic index to assess the eco-efficiency of a sample of 36 DWTPs from a holistic approach. This index integrates three key variables such as the volume of water produced and its quality, operational costs, and GHG emissions. The Efficiency Analysis Trees (EAT) method has been applied which, unlike other traditional multi-criteria approaches, also allows estimating optimal operating costs and GHG emissions based on varying produced water volumes. Results reveal substantial variations in optimal operating costs and GHG emissions, ranging from \$0.023 to \$0.519 per cubic meter and 0.050 kgCO_2 equivalent to 0.584 kgCO_2 equivalent per cubic meter, respectively. These divergences were also evident in the potential savings in operational costs, which ranged from \$0.013 to \$0.044 per cubic meter, and in the reductions in greenhouse gas (GHG) emissions, which varied between 0.005 gCO_2 equivalent and 67.899 gCO_2 equivalent. The average eco-efficiency score among the DWTPs was 0.595, ranging from 0.022 to 1.000. The number of eco-efficient DWTPs was 7 representing 19.4% of the sample. Variability in the performance of DWTPs underscores the limitations of uniform regulatory targets, advocating for customized targets that consider individual DWTP capacities.

1. Introduction

Climate change and increasing population growth and urbanization are exerting significant pressure on global water resources (United Nations, 2024). Currently, approximately two billion people lack access to safe drinking water (SDG Report, 2022), and about half of the global population faces severe water scarcity for at least part of the year (IPCC, 2022). On the other hand, the United Nations declared access to clean and safe water as a fundamental human right (United Nations, 2010). Additionally, the Sustainable Development Goal 6 calls for ensuring availability and sustainable management of water and sanitation for all (UN, 2015; Pereira and Marques, 2022). The delivery of drinking water involves the use of significant energy for abstraction, treatment, and distribution (Sowby and Siegel et al., 2024; WAREG, 2023). This energy usage results in Scope 2 greenhouse gas (GHG) emissions, which are associated with the indirect consumption of energy, including the procurement of electricity, steam, heat, or cooling (EPA, 2023).

Drinking water treatment processes are recognized as major contributors to energy consumption (Plappally and Lienhard V, 2012) and GHG emissions throughout the lifecycle of a water treatment facility (Zib et al., 2021). Assessing the carbon emissions linked to drinking water treatment is crucial for achieving a net-zero GHG urban water cycle (Yateh et al., 2024). Reducing the energy intensity in drinking water facilities and increasing the proportion of energy sourced from renewables is essential to reduce the carbon footprint of drinking water services (EurEau, 2019). At the same time, ensuring that water services are affordable remains a priority (United Nations, 2010; Molinos-Senante et al., 2022). Recent studies suggest that adopting cooperative approaches that integrate economic and environmental considerations can enhance the decision-making processes related to the provision of water services, ultimately leading to more efficient and sustainable outcomes (Ananda, 2019; Chini et al., 2020).

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As reviewed by Yateh et al. (2024), numerous studies have explored the energy consumption and carbon emissions of drinking water treatment plants (DWTPs), focusing primarily on estimating carbon emissions through life cycle analysis (Beeftink et al., 2021; Singh et al., 2021) and evaluating their shadow prices (Molinos-Senante and Guzmán, 2018). This analysis allows assessing the environmental impacts of DWTPs but does not provide insights into economic performance. Other research has examined the energy usage of DWTPs by employing various technological approaches (Chew et al., 2016; Grzegorzek et al., 2023). These studies offer valuable insights for comparing the performance of DWTPs in terms of energy use. However, they do not account for the quality of either the raw water or the drinking water produced. To overcome this limitation, an alternative line of research has employed multi-criteria analysis to assess the energy efficiency (Ananda, 2018; Maziotis et al., 2023a; Maziotis and Molinos-Senante, 2024) and carbon efficiency (Maziotis et al., 2023b) of DWTPs. These studies primarily defined efficiency as the performance of DWTPs in terms of energy use or GHG emissions per unit of water treated.

Previous studies estimating energy and carbon efficiencies of DWTPs have not considered both variables—energy use and carbon emissions—simultaneously. In other words, these studies evaluated the performance of DWTPs either in terms of energy use or carbon emissions, but not both concurrently. As a result, there are no prior studies that assess the eco-efficiency of DWTPs using multi-criteria methods. Assessing the eco-efficiency of DWTPs presents several challenges and difficulties. Some of the most significant are as follows. Firstly, from a methodological perspective, there is no universally accepted approach for evaluating eco-efficiency in water facilities. Various methodologies, such as life cycle assessment and multi-criteria decision analysis, can be applied, each with its own advantages and limitations. Balancing environmental impact assessments with economic indicators remains a key challenge, as a multidimensional approach is required. Secondly, data availability poses a significant challenge. Many water utilities do not systematically collect essential environmental and economic data on DWTPs, resulting in data gaps and inconsistencies that hinder comprehensive eco-efficiency assessments. Finally, differing stakeholder perspectives—including those of water utilities, regulators, and consumers—can lead to conflicting priorities, influencing how eco-efficiency is measured and integrated into decision-making processes.

Eco-efficiency is defined as a comprehensive performance assessment that combines multiple factors into a synthetic index. The synthetic index proposed in this study, i.e., eco-efficiency score, integrates the volume of drinking water produced, its associated quality, operational costs, and GHG emissions, thus addressing the potential trade-offs between operational costs and GHG emissions required to produce a specified volume of drinking water. In the context of wastewater treatment plants, it has been demonstrated that effluent quality, operational cost, and GHG emissions can be conflicting objectives (Arnell et al., 2017). Therefore, integrating these three key variables—volume of water produced, operational costs, and GHG emissions—into a synthetic index to represent the eco-efficiency of each DWTP is crucial for enhancing the performance of these facilities from a holistic perspective.

The integration of water quality—whether of the raw water or the drinking water produced—is a critical aspect when assessing the eco-efficiency of DWTPs. However, this variable has often been overlooked in previous studies. Ignoring water quality can result in misleading conclusions about a DWTP's eco-efficiency, as producing high-quality drinking water typically requires greater energy consumption and higher operational costs. Therefore, incorporating water quality is essential to ensure that performance indices reflect a comprehensive evaluation of both quantity and quality (Gibellni et al., 2024). To address this challenge, in this study, the volume of water produced by each assessed DWTP was adjusted using a quality indicator provided by the water regulator. This adjustment ensures that the eco-efficiency assessment accounts for both the quantity of water produced and its quality.Against this background, the primary goal of this study is to evaluate the eco-efficiency of a selection of DWTPs, providing a comprehensive assessment of their performance that integrates the volume of water produced and its quality, operational costs, and GHG emissions. Furthermore, the novel methodological approach outlined in section 2 achieves two additional objectives: (i) quantifying the potential savings in production costs and reductions in GHG emissions that could be realized if DWTPs operated eco-efficiently, and (ii) determining the optimal levels of operating costs and GHG emissions for varying volumes of water produced.

Previous research has evaluated the energy and carbon efficiency of DWTPs independently. However, these critical parameters have not been synthesized into a comprehensive index that reflects the holistic performance of DWTPs from both a technical and environmental perspective. This study addresses this gap by assessing, for the first time, the eco-efficiency of DWTPs using an integrated framework. The analysis incorporates key variables such as water production volume, water quality, operational costs, and GHG emissions, providing valuable insights into the trade-offs among these interconnected factors. To achieve this, a novel methodological approach combining machine learning and linear optimization techniques was employed. This innovative approach not only facilitates the assessment of eco-efficiency but also enables the derivation of optimal operational cost structures and GHG emission levels for various treatment volumes. This dual focus on optimization and integration represents a significant advancement in the literature on sustainable water treatment.

The findings of this study are critical for informing the development of policies aimed at enhancing the sustainability of DWTPs. By quantifying and balancing the trade-offs among cost efficiency, environmental impact, and water quality, this research offers a robust foundation for decision-makers to improve the performance of DWTPs.

2. Methodology

2.1. Eco-efficiency assessment and estimation of optimal levels of operating costs and GHG emissions

The eco-efficiency of a sample of DWTPs was assessed using the Efficiency Analysis Trees (EAT) method, which merges machine learning with linear programming techniques (Esteve et al., 2020) according to the flowchart shown in Fig. 1.

The machine learning technique used is based on Classification and Regression Tree (CART) (Breiman et al., 1984). CART partitions the dataset into distinct clusters by identifying threshold values of predictor variables (e.g., water production volumes). These splits are designed to minimize the mean squared error (MSE) within each node, ensuring that units within the same cluster exhibit similar characteristics in terms of operational costs and GHG emissions. The resulting clusters effectively divide the input-output space into distinct subspaces. These subspaces, in turn, define the feasible regions for the subsequent linear programming models. Each linear programming model, applied to a specific cluster, assumes that the production possibilities within that cluster are constrained by the observed performance of the units it contains (Jin and Xu, 2024a). In other words, the clusters generated by CART limit the feasible solution space explored by the linear programming models, ensuring that the optimization process remains grounded within the observed operational boundaries.

Linear programming is applied to compute eco-efficiency scores of each DWTP in each cluster previously defined according to the CART approach. It allows maximizing eco-efficiency within constrains as in traditional techniques such as Data Envelopment Analysis (DEA). However, unlike DEA, which is the most commonly used multi-criteria method for assessing the energy efficiency of DWTPs (Ananda, 2018; Maziotis et al., 2023a), the EAT method does not suffer from overfitting issues. Overfitting occurs when a model is excessively tailored to a specific dataset, potentially compromising the robustness of the efficiency scores (Maziotis and Molinos-Senante, 2024). Esteve et al. (2020,

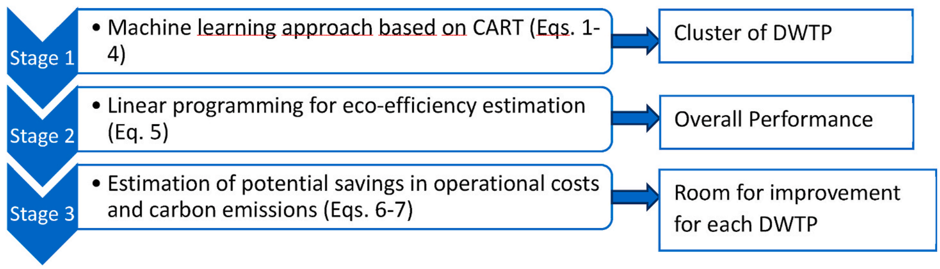

Fig. 1. Flowchart of the methodological approach.

2021) demonstrated that the EAT method provides more reliable measurements of efficiency as it does not present overfitting problems.

The nomenclature used in this study is shown in Table 1.

Let's assume that the sample consists of several predictors presented as $x_1, \dots, x_m$ with $x_i \in R^m$. This set of predictors is used to estimate a set of response factors denoted as $y, \dots, y_n$ with $y_i \in R^n$. The EAT technique allows selecting a predictor factor j and a threshold $s_j \in S_j$ where S_j presents the set of likely thresholds for the variable j to split up the sample into two nodes, the right and the left node respectively, t_R and t_L (Maziotis and Molinos-Senante, 2024). This is done through the use of the MSE (Jin and Xu, 2024b). Mathematically, this is presented as follows (Zofio et al., 2024):

$$R(t_L)+R(t_R)=\frac{1}{n}\sum_{(x_i,y_i)\in t_L}(y_i-y(t_L))^2+\frac{1}{n}\sum_{(x_i,y_i)\in t_R}(y_i-y(t_R))^2 \quad (1)$$

where n is the sample size, the left and right nodes of the tree are presented by t_L and t_R, respectively, $R(t)$ is the MSE of each node t, $y(t_L)$ and $y(t_R)$ are the estimated maximum values of the response variables reported in the two nodes (Molinos-Senante et al., 2023).

The values of the response variables, $y(t_L)$ and $y(t_R)$ are defined as follows:

$$y(t_L)=max\left\{max\{y_i:(x_i,y_i)\in t_L\},y\left(I_{T(k|t^*\to t_L,t_R)}(t_L)\right)\right\} \quad (2)$$

$$y(t_R)=max\left\{max\{y_i:(x_i,y_i)\in t_R\},y\left(I_{T(k|t^*\to t_L,t_R)}(t_R)\right)\right\} \quad (3)$$

In Eqs. (2) and (3), the EAT algorithm produces the sub-tree T, the number of splits are presented by k, $y\left(I_{T(k|t^*\to t_L,t_R)}(t_L)\right)$ and $y\left(I_{T(k|t^*\to t_L,t_R)}(t_R)\right)$ are the set of nodes of the tree obtained from fulfilling the $k-$ th split that Pareto dominates node t_L and t_R (Rebai et al., 2019).

The production technology estimated by the EAT technique is outlined as follows:

$$\widehat{PT_{T_k}}=\left\{(x,y)\in R_+^{m+1}:y\le d_{T_k}(x)\right\} \quad (4)$$

where the predictor related to the sub-tree T_k is denoted by $d_{T_k}(x)$.

The estimation of the eco-efficiency score of each unit (DWTP) is obtained by solving the following linear programming model:

$$\varphi^{EAT}(x_k,y_k)=\max\varphi \quad (5)$$

$$s.t.$$

$$\sum_{t\in\tilde{T}^*}\lambda_t a_j^t\le x_{jk}, j=1,\dots,m$$

$$\sum_{t\in\tilde{T}^*}\lambda_t d_{rT^*}^t(a^t)\ge\varphi y_{jk}, r=1,\dots,p$$

$$\sum_{t\in\tilde{T}^*}\lambda_t=1$$

$$\lambda_t\in\{0,1\}, i=1,\dots,n$$

where φ^{EAT} represents the eco-efficiency score for each DWTP being evaluated. The term $(a^t, d_{T^*}(a^t))$ denotes points in the input-output space for all $t\in T^*$, where * specifies the final sub-tree. The λ are intensity variables, which are used to determine the linear combinations of the inputs and outputs that define the efficient frontier (Molinos-Senante et al., 2022b). The third constraint in Eq. (5) ensures that eco-efficiency scores are estimated assuming variable returns to scale (VRS) technology. Considering the diversity of capacity, i.e., volume of drinking water produced, of the assessed DWTPs, this assumption is more appropriate than assuming constant returns to scale technology. The VRS assumption allows for the incorporation of scale effects into the eco-efficiency assessment, enabling a more accurate evaluation of how different scales of operation influence eco-efficiency (Ananda, 2019).

The eco-efficiency score (φ^{EAT}) is a synthetic index that ranges from zero to one, with a score of one indicating that the DWTP is fully eco-efficient. It represents optimal performance among the sample of evaluated facilities. Scores less than one indicate the presence of eco-inefficiency, suggesting that there are opportunities for improvement in the DWTP's operations to enhance both its economic efficiency and environmental performance.

Based on the eco-efficiency scores derived from Eq. (5), it is possible to estimate the potential savings in operating costs and GHG emissions that each DWTP could achieve if it operated at full efficiency. These savings represent the difference between the current performance of each facility and the best performers within the assessed sample.

$$Operating\ costs_s=Operating\ costs_c{}^*\left(1-\varphi^{EAT}\right) \quad (6)$$

$$Greenhouse\ gas\ emissions_s=Greenhouse\ gas\ emissions_c{}^*\left(1-\varphi^{EAT}\right) \quad (7)$$

where $Operating\ costs_s$ denote the potential savings in operating costs that a DWTP could obtain if it was fully eco-efficient; $Operating\ costs_c$

Table 1
Summary of the nomenclature used.

Variable	Meaning	Type
x_i	Predictor	Continuous
y_i	Response factor	Continuous
S_j	Thresholds for variable j	Continuous
t_R	Right node	
t_L	Left node	
n	Sample size	Continuous
$R(t)$	Mean squared of error of node t	Continuous
$y(t_L)$	Estimated maximum value of response factor at left node	Continuous
$y(t_R)$	Estimated maximum value of response factor at right node	Continuous
k	Number of splits	Continuous
φ^{EAT}	Eco-efficiency scores	[0–1]
λ	Intensity variables	[0–1]
$Operating\ costs_s$	Potential savings in operating costs	Continuous
$Operating\ costs_c$	Current operating costs	Continuous
$Greenhouse\ gas\ emissions_s$	Potential savings in greenhouse gas emissions	Continuous
$Greenhouse\ gas\ emissions_c$	Current greenhouse gas emissions	Continuous

present the observed (actual) operating costs for each DWTP; *Greenhouse gas emissions*$_s$ denote the reduction in GHG emissions that a DWTP could obtain if it was fully eco-efficient and *Greehouse gas emissions*$_c$ are the actual levels of GHG emissions for each DWTP included in the analysis.

To gain a better understanding of potential structural and operational characteristics influencing eco-efficiency scores of DWTPs, non-parametric tests such as the Mann-Whitney test (for two groups) or the Kruskal-Wallis test (for three or more groups) were employed. The DWTPs were categorized into groups based on various factors, including the year of establishment, the main source of raw water, the presence of a catch basin, and whether they employ a coagulation-flocculation process. The null hypothesis for these tests was that there are no differences in the eco-efficiency scores among the predefined groups of DWTPs (Molinos-Senante and Guzmán, 2018). A *p*-value less than 0.05 from these tests indicates that the null hypothesis can be rejected, suggesting that the eco-efficiency scores differ significantly among the groups. This level of significance, with a confidence of 95%, allows for robust conclusions about the influence of the tested variables on the eco-efficiency of DWTPs (Yan et al., 2024).

2.2. Data and sample selection

The identification of outliers and atypical observations is essential for accurately assessing the relative performance of units, as these can lead to overestimations or underestimations of eco-efficiency scores (Ferreira et al., 2023). To address this issue, a peer index approach (De Witte and Marques, 2010) was applied to the original database, which included 51 DWTPs. This method facilitated the identification of 15 DWTPs as outliers, which were subsequently removed from the analysis. As a result, the eco-efficiency of the remaining 36 facilities was evaluated, ensuring a more reliable and representative assessment of performance across the sample.

The 36 DWTPs evaluated in this study comply with the standards set forth by the Chilean law NCh409/1, which defines the quality requirements for drinking water. This regulation encompasses 46 parameters categorized into five groups: i) microbiological and turbidity parameters; ii) chemical components relevant to human health; iii) radioactive parameters; iv) organoleptic parameters; and v) disinfection parameters. According to the Chilean regulatory framework for the water industry, the supervision of drinking water quality is carried out jointly by the operators of the DWTPs and the Chilean water regulator, the Superintendencia de Servicios Sanitarios (SISS) (SISS, 2023). The 36 DWTPs evaluated in this study operate under this unified regulatory framework. The EAT method and other non-parametric approaches such as DEA do not allow for the integration of contextual variables in performance assessment. Consequently, the estimated results (optimal costs and GHG emissions and eco-efficiency scores) do not account for external factors affecting the DWTPs. This limitation is one of the reasons the sample was restricted to 36 DWTPs. The selected facilities were chosen to ensure the greatest possible homogeneity concerning external factors. However, variations still existed among the assessed facilities in terms of construction year, primary raw water source, and the presence or absence of catchment basins. Therefore, a second stage of analysis, the results of which are detailed in Section 3.3, was conducted. These minor differences among DWTPs are also evident in certain operational variables, where the minimum and maximum values show significant variation (see Table 2).

The raw water sources for these facilities vary based on their location and water availability, with groundwater serving as the source for 27 DWTPs and surface water for 8 DWTPs. Although the main unit processes at the 36 DWTPs are generally similar, 8 of them include a catch basin to homogenize the quality of the raw water entering the treatment plants. Additionally, due to the adequate quality of the raw water, 12 out of the 36 DWTPs do not perform coagulation-flocculation processes to remove pollutants.

The variables selected to assess the eco-efficiency of DWTPs were based on data availability and previous research in this field (Molinos-Senante and Guzman, 2018; Cetrulo et al., 2019; Goh and See, 2021; Sowby and Hales, 2022). The response variables chosen were: i) Operating expenditure (OPEX) measured in US dollars per year for each DWTP, reflecting the direct costs associated with the operation of the facilities and; ii) Scope 2 GHG emissions which are related to indirect energy consumption, including the purchase of electricity, steam, heat, or cooling (EPA, 2023). The emissions are quantified in kilograms of CO_2 equivalent (CO_{2eq}). The calculation of indirect GHG emissions was based on the energy usage of each DWTP and considers the average weighted emission factor for electricity in Chile, which was 418.70 kg CO_{2eq}/MWh in 2018 (Chilean Ministry of Energy, 2018).

The predictor variable is the volume of drinking water produced by each DWTP, measured in cubic meters per year. To adjust for water quality, this volume is multiplied by a synthetic quality indicator provided by the national regulator (SISS). This indicator ranges from zero to one, where a value of one indicates that the drinking water meets all quality tests associated with parameters such as bacteriology, turbidity, and free residual chlorine (Molinos-Senante and Guzman, 2018; Molinos-Senante et al., 2022). This adjustment allows for a more nuanced analysis of water production in relation to its quality, providing a comprehensive view of each DWTP's performance. Table 2 presents the descriptive statistics for the variables utilized in the study, with data sourced from the national regulator, SISS. The data used in this study is not publicly available but can be requested from the SISS through the Chilean public transparency data system.

3. Results and discussion

3.1. Optimal operational costs and greenhouse gas emissions

The regression tree from the EAT method, depicted in Fig. 2, provides an analysis of optimal OPEX and Scope 2 GHG emissions for DWTPs based on their annual water production volumes. The tree identifies key production thresholds that influence the maximum allowable OPEX and GHG emissions: i) Large size facilities whose production is larger than 7,677,685 m^3/year. For these plants, the maximum levels of OPEX and GHG emissions are US$344,075 and 806,782 $kgCO_{2eq}$, respectively, translating to US$0.045 per m^3 and 0.105 $kgCO_{2eq}$ per m^3; ii) Medium size facilities producing between 662,613 m^3/year and 7,677,685 m^3/year. The maximum level of OPEX estimated is US$344,075, with costs ranging from $0.045 to $0.519 per m^3 depending on specific production volumes within this range. On the other hand, maximum GHG emissions levels are 387,065 $kgCO_{2eq}$, resulting in emissions ranging from 0.050 to 0.584 $kgCO^{2eq}$ per m^3 and; iii) Small size facilities whose production of drinking water is less than 662,613 m^3/year. In this segment, the maximum annual level of OPEX is US$15,880, corresponding to a minimum of $0.023 per m^3. Moreover, the maximum annual levels of GHG emissions are 81,445 $kgCO_{2eq}$,

Table 2
Descriptive statistics of the drinking water treatment plants evaluated.

Variables	Unit of measurement	Mean	Standard Deviation	Minimum	Maximum
Operational costs	US$/year	282,103,430	465,145,549	73,656	2,094,381,219
Quality adjusted volume of water	10^3 m^3/year	17,155,555	59,638,214	30,624	344,633,664
Greenhouse gas emissions	kg CO_{2eq}/year	109,004	165,263	2986	806,782

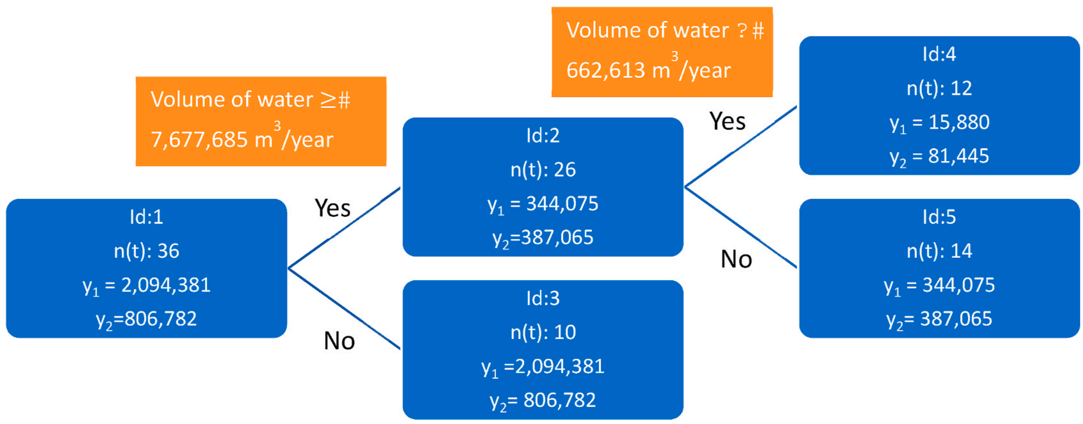

Fig. 2. Efficiency Analysis Tree (EAT) for estimating optimal operating costs and greenhouse gas emissions, *where*: *Id denotes the node*; *n(t) shows the number of observations*, *y_1 is the maximum operating costs in US$* per *year and y_2 is the maximum level of greenhouse gas emissions in kg of $CO2_{eq}$* per *year.*

leading to a minimum emission rate of 0.123 $kgCO_{2eq}$ per m^3.

Results shown in Fig. 2 highlight the variability in optimal OPEX and GHG emissions across DWTPs of different sizes, with OPEX ranging from US$0.023 to US$0.519 per m^3 and GHG emissions from 0.050 to 0.584 $kgCO_{2eq}$ per m^3. These results have several policy implications for sustainable drinking water production, particularly in balancing operational costs and GHG emissions across different scales of water production facilities. Firstly, policymakers and water managers might consider promoting the development of larger DWTPs where feasible, to capitalize on these economies of scale. However, this strategy must be balanced against potential risks to urban drinking water resilience, as reliance on fewer, larger facilities could increase vulnerability to operational disruptions (Garrido-Baserba et al., 2024). Furthermore, the current regulatory framework in Chile does not differentiate between facilities based on size, applying uniform standards across all DWTPs. This approach could be reevaluated to introduce tiered regulation and incentives that reflect the scale of operations. Such a regulatory adjustment could entail stricter GHG emission limits and cost controls for larger facilities, which have demonstrated lower per-unit emissions and operational costs. Conversely, smaller facilities might benefit from more supportive measures or temporarily relaxed standards to facilitate necessary investments aimed at enhancing efficiency and reducing emissions. Lastly, establishing performance benchmarks derived from the thresholds identified through decision tree analysis could serve as a valuable regulatory tool. These benchmarks would enable regulators and industry stakeholders to motivate and monitor the performance of water facilities more effectively, encouraging them to strive towards optimal economic and environmental outcomes.

3.2. Eco-efficiency estimations and potential OPEX and GHG reductions

The analysis of eco-efficiency scores for individual DWTPs as depicted in Fig. 3 indicates an average eco-efficiency score of 0.595. However, substantial variability among the evaluated facilities is evident from Fig. 4. Specifically, 12 out of the 36 plants, representing 33% of the sample, achieved high standards, with eco-efficiency scores averaging above 0.81. Further breakdown of the results reveals that 7 DWTPs, accounting for 19% of the sample, were fully eco-efficient. These facilities are the top performers and serve as benchmarks for the rest. The DWTPs identified as eco-efficient are heterogeneous in terms of size and exogenous factors such as age, source of raw water, and the number of unitary processes. This highlights that local context (Paraschiv et al., 2023) and managerial decisions (Molinos-Senante and Farías, 2018) play crucial roles in the performance of urban water

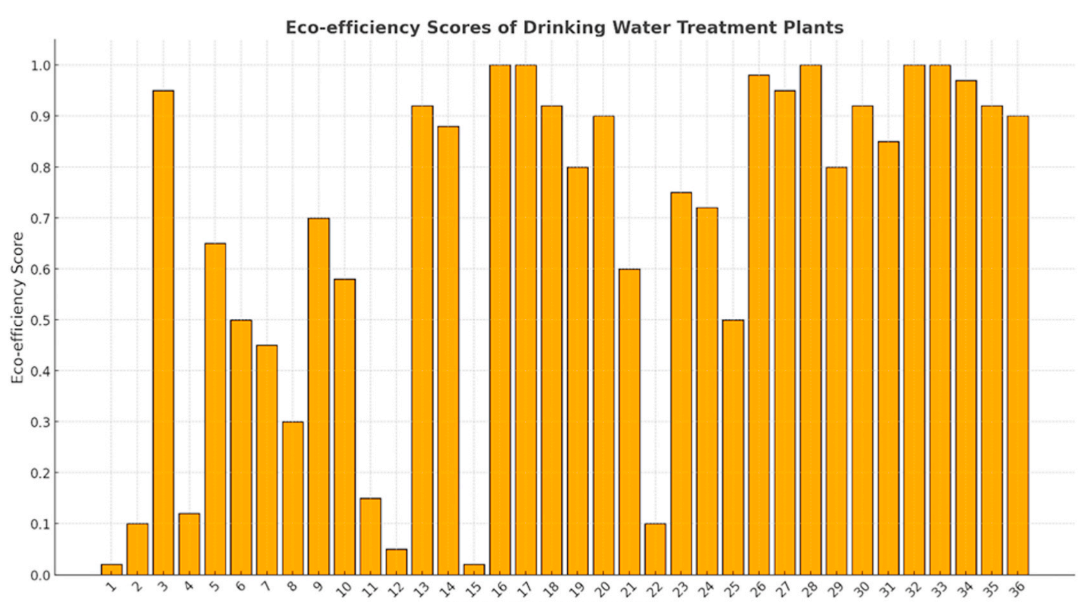

Fig. 3. Eco-efficiency score of each drinking water treatment plant assessed.

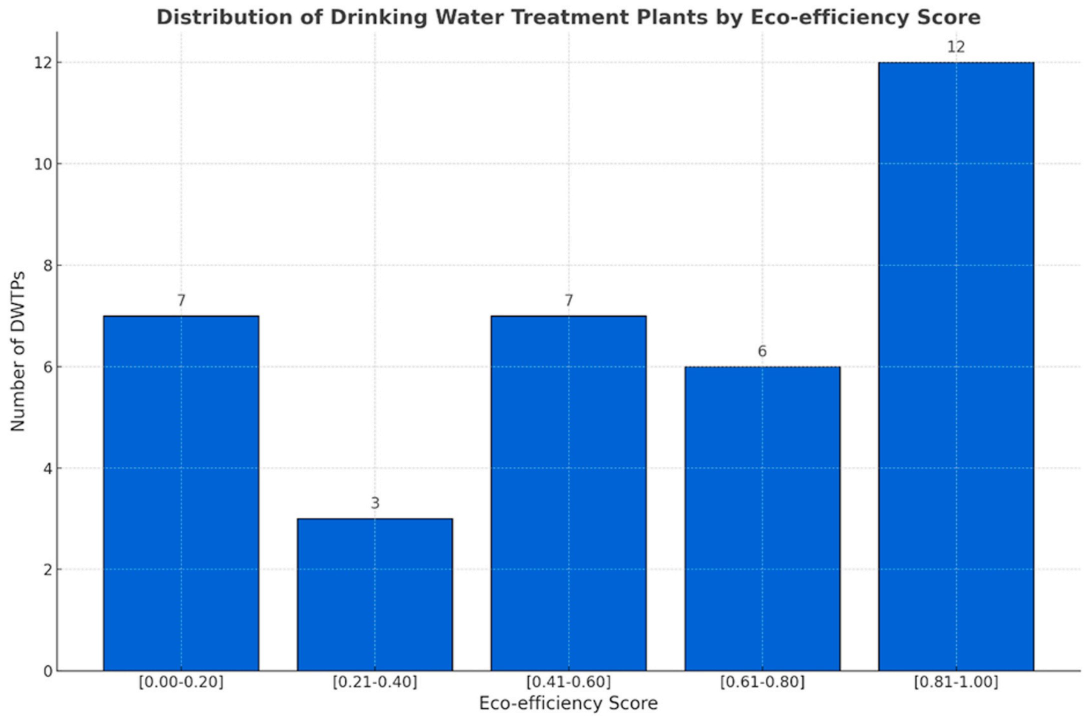

Fig. 4. Histogram with the distribution of eco-efficiency scores across DWTPs.

systems.

Another 6 plants, constituting 17% of the sample, had moderate eco-efficiency scores ranging from 0.61 to 0.80, indicating good but improvable efficiency levels. Conversely, the performance of several plants was notably poor in terms of eco-efficiency. Specifically, 10 plants, or 28% of the sample, scored less than 0.40, with the majority of these being particularly eco-inefficient, reporting an average score of less than 0.20. Specifically, 7 DWTPs exhibit eco-efficiency scores below 0.20. All these facilities are situated in the Metropolitan Region of Santiago, the capital city of Chile, and are operated by three water companies belonging to the same economic group. Given that the eco-efficiency scores of other DWTPs in the same region, but operated by different water companies, are higher, this suggests that the low performance of these facilities is likely due to managerial issues rather than regional or contextual factors.

The segmentation in eco-efficiency scores among the 36 assessed DWTPs highlights the need for targeted improvements and potential restructuring in operational practices for these lower-performing facilities to enhance their overall eco-efficiency.

The estimation of eco-efficiency scores at the facility level provides an individual quantification of the potential reductions in OPEX and GHG emissions achievable if the facilities operated at full eco-efficiency (Eqs. (6) and (7)). For a more straightforward comparison among facilities, these potential savings in OPEX and GHG emissions are

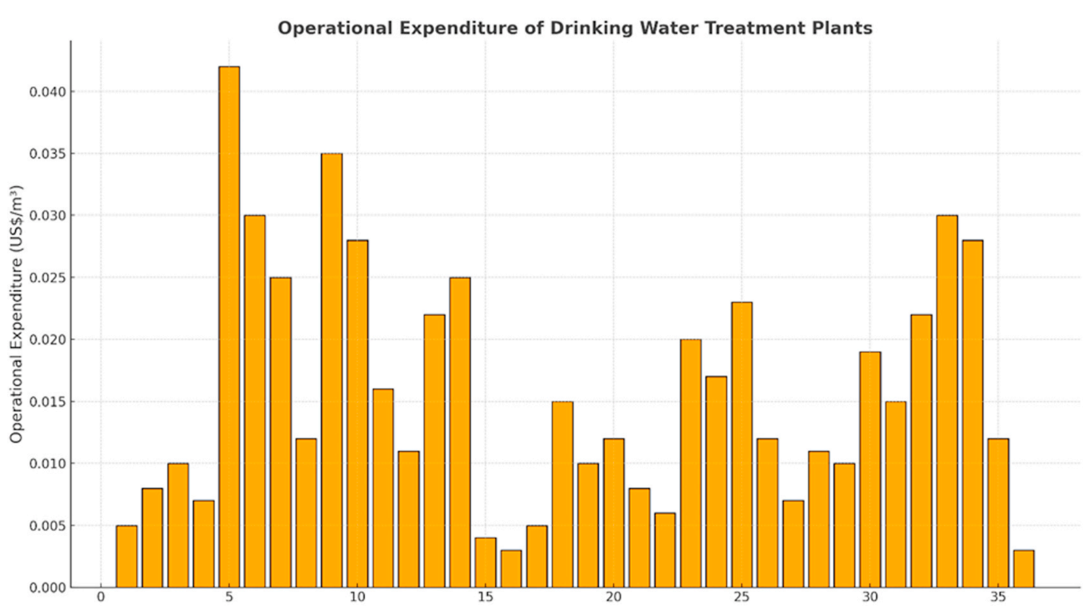

Fig. 5. Potential operational expenditure savings if drinking water treatment plants were eco-efficient.

expressed in US$ and grams of CO_{2eq} per cubic meter of drinking water produced, as shown in Figs. 5 and 6 respectively. In terms of OPEX, the average potential savings, excluding the seven eco-efficient DWTPs, amounted to US$0.013 per cubic meter, with a range from a maximum of US$0.044 to a minimum of US$$1.3*10^{-6}$ per cubic meter (Fig. 5). If all eco-inefficient facilities were to achieve eco-efficiency, it could result in potential annual savings of approximately US$5,272,287. This represents 52% of the total OPEX for the 36 evaluated DWTPs, underscoring significant opportunities for cost reductions. According to the regulatory model applied in Chile by the urban water regulator, any reductions in operational costs achieved by water companies must be passed on to customers (SISS, 2023). Therefore, improvements in the eco-efficiency of DWTPs that lead to reductions in OPEX would directly benefit customers through lower water tariffs.

The potential reductions in GHG emissions for eco-inefficient DWTPs, as depicted in Fig. 6, highlight significant opportunities for environmental improvement. Excluding the eco-efficient DWTPs, which already operate at optimal carbon efficiency, the average potential reduction in GHG emissions is 17.895 g CO_{2eq} per cubic meter of treated water. However, there is a wide range of variability among these facilities, with potential reductions spanning from 0.005 g CO_{2eq}/m^3 to 67.899 g CO_{2eq}/m^3. When these reductions are scaled up to the total volume of drinking water produced by each facility, the cumulative potential savings in Scope 2 GHG emissions amount to 2,038,926 kg CO_{2eq} per year. To put this figure into perspective, considering the per capita GHG emissions balance in Chile, which was 3.09 metric tons of CO_{2eq} per year in 2018 according to the Chilean Environment Ministry (2014), the total potential reduction in emissions from these DWTPs is equivalent to the annual emissions of approximately 660 Chileans.

3.3. Factors influencing eco-efficiency scores and potential OPEX and GHG reductions

In this section we aim to get a better understanding of eco-efficiency of DWTPs by grouping them based on operational and structural characteristics to identify statistically significant differences. Table 3 presents how eco-efficiency correlates with the construction age of the plants. The findings reveal that facilities constructed post-1960 exhibit greater eco-efficiency compared to their older counterparts. Specifically, plants established between 1960 and 1975 and after 1995 demonstrate the highest eco-efficiency levels, with these differences being statistically significant, as indicated by a Kruskal-Wallis p-value of 0.023. However, these results should be interpreted cautiously due to the varying number of facilities in each category. Additionally, the lack of data on infrastructure updates since construction means some observed differences might also be due to varying maintenance practices across DWTPs. It is important to note that eco-inefficiency scores affect potential OPEX and GHG emissions differently, given the current cost and emission variations among facilities. Table 3 illustrates that higher eco-inefficiency does not necessarily imply significant opportunities for improvement.

Table 3
Eco-efficiency and savings by year built.

Year built	Number of DWTPs	Average Eco-efficiency	Average cost savings (US $/m^3$)	Average GHG savings (gCO_{2eq}/m^3)
[1946–1960)	3	0.150	0.009	5.845
[1960–1975)	2	0.727	0.009	6.461
[1975–1995)	10	0.454	0.019	2.978
[>1995)	21	0.714	0.007	21.844

Table 4 illustrates the association between eco-efficiency and the primary water source used by DWTPs. The data reveal that plants who source water from surface bodies demonstrate higher eco-efficiency levels compared to those who extract water from groundwater sources, with these differences being statistically significant (Mann-Whitney test p-value of 0.034). This difference may be linked to the higher energy demands required for extracting water from groundwater sources such as boreholes, which directly influence Scope 2 GHG emissions. Consequently, this highlights the importance of considering environmental variables impacting facilities before establishing uniform standards or regulations across all DWTPs. Although there are significant differences in average eco-efficiency scores between the two groups of facilities,

Table 4
Eco-efficiency and savings based on water source.

Source of water	Number of DWTPs	Average Eco-efficiency	Average cost savings (US $/m^3$)	Average GHG savings (gCO_{2eq}/m^3)
Surface	9	0.837	0.010	14.334
Groundwater	27	0.515	0.011	14.443

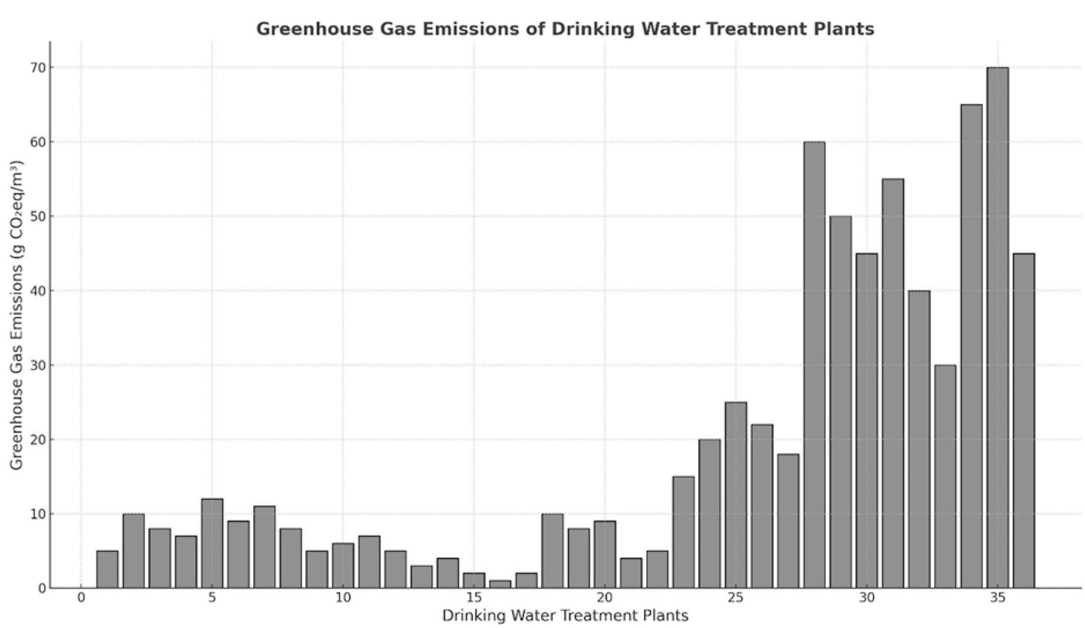

Fig. 6. Potential greenhouse gas emissions reductions if drinking water treatment plants were eco-efficient.

these differences are not reflected in potential OPEX savings or reductions in GHG emissions, given the existing levels of these variables. This observation underscores the necessity for regulatory policies that are tailored to enhance the performance of facilities, taking into account both the top performers and the unique characteristics of each plant.

Table 5 shows the relationship between eco-efficiency and the integration of two specific unitary processes in DWTPs such as catch basins and coagulation-flocculation. For plants incorporating a catch basin, it is observed that they tend to have lower average eco-efficiency scores, with the differences being statistically significant as indicated by a Mann-Whitney test p-value of 0.045. However, this lower eco-efficiency does not necessarily translate into greater opportunities for cost savings or reductions in GHG emissions, considering the current levels of these variables. In contrast, while DWTPs lacking the coagulation-flocculation process exhibit higher average eco-efficiency scores, the differences are not statistically significant, with a Mann-Whitney test p-value of 0.120. Therefore, from a statistically perspective the absence or presence of the coagulation-flocculation process does not significantly impact eco-efficiency scores.

Given the low eco-efficiency reported for a significant number of DWTPs, the Chilean water regulator should consider introducing policies that incentivize improved managerial practices through performance-based regulatory frameworks. A notable example is the English and Welsh water regulator which recognizes and rewards high-performing operators during the process of setting water tariffs (Ofwat, 2024). Considering the impact of infrastructure age on DWTPs' eco-efficiency, funding mechanisms should be established to support the modernization and maintenance of older facilities. Given the regulatory and ownership structure of water infrastructure in Chile, various approaches, such as public-private partnerships or new concession models, could be explored. As DWTPs who source water from surface sources tend to be more eco-efficient than those relying on groundwater, regulatory frameworks should account for the higher energy demands associated with groundwater extraction. To mitigate these demands, strategies such as the implementation of energy recovery systems or the integration of renewable energy sources should be promoted. These measures would enhance eco-efficiency while aligning with broader sustainability goals. From a managerial perspective, DWTPs can adopt several strategies to enhance their eco-efficiency. Energy use constitutes a significant portion of the total operational costs of DWTPs (WAREG, 2023). Hence, reducing energy consumption would positively impact eco-efficiency from both economic and carbon perspectives. This can be achieved through the optimization of key energy-intensive equipment such as ensuring the proper operation and maintenance of pumping systems. Conducting regular energy audits and setting internal energy-saving targets are additional effective measures to reduce energy use. These strategies are not dependent on the size of the infrastructure and should be a priority for all operators. Nevertheless, specific priorities may vary based on the unique circumstances of each water service provider (EurEau, 2019). To further reduce GHG emissions and improve eco-efficiency, transitioning from electricity generated from fossil fuels to renewable energy sources is essential. In cases where topography allows, mechanical energy from raw or treated water flowing downhill can be harnessed using turbines to generate power. Additionally, DWTPs often have substantial physical footprints, providing opportunities to develop solar and wind energy systems as alternative energy sources, depending on the site's environmental conditions.

4. Conclusions

DWTPs are significant contributors to energy use and GHG emissions throughout the lifecycle and operation of a water treatment facility, and their operation also incurs considerable costs. Assessing the eco-efficiency of DWTPs through a synthetic index that integrates the volume of water produced, its quality, operational costs, and GHG emissions is essential for a deeper understanding of the water-energy-carbon nexus in these facilities. In this study, we employed the EAT method to assess the eco-efficiency of a sample of 36 DWTPs. Unlike other multi-criteria methods, EAT also facilitates the derivation of optimal operating costs and GHG emissions for various volumes of water produced.

The results of the case study underscore the necessity of considering the capacity of DWTPs when setting economic and environmental targets by water regulators. The findings indicate that optimal operating costs vary significantly, ranging from \$0.023 to \$0.519 per cubic meter, while optimal GHG emissions range from 0.050 $kgCO_{2eq}$ to 0.584 $kgCO_{2eq}$ per cubic meter, depending on the volume of water produced. This variation highlights the inadequacy of imposing uniform targets across all facilities, suggesting that tailored objectives are more appropriate. In terms of overall performance, the average eco-efficiency score among the DWTPs was 0.595, with 7 out of 36 plants (19%) classified as eco-efficient. However, there were considerable variations in eco-efficiency scores across the DWTPs, indicating divergent starting points for different facilities. Consequently, the efforts and measures required to move towards eco-efficiency vary significantly among them. This divergent performance is also evident in the potential operational cost savings and GHG emissions reductions. Operational cost savings ranged from a minimal US$\$1.3*10^{-6}$ per cubic meter to \$0.044 per cubic meter, and GHG emissions reductions varied from 0.005 gCO_{2eq} per cubic meter to 67.889 gCO_{2eq} per cubic meter. These findings emphasize the need for customized approaches to improve the sustainability and efficiency of DWTP operations, tailored to the specific conditions and capabilities of each facility.

Based on the case study results some policy implications for the management and regulation of DWTPs to enhance their eco-efficiency are as follows. Firstly, the water regulator should consider implementing flexible, DWTP-specific targets that account for the unique conditions and capacities of each facility. This approach would enable more realistic and achievable benchmarks for each DWTP. Given the varying eco-efficiency scores, incentives provided by the water regulator could be structured to reward improvements relative to each plant's starting point. This would encourage facilities with lower baseline scores to make significant enhancements, thereby promoting greater overall system eco-efficiency. Finally, establishing programs for capacity building and the dissemination of best practices among DWTPs can help leverage the knowledge gained from high-performing plants. This would facilitate a collaborative approach to problem-solving and innovation in water treatment processes.

While this study provides significant contributions to understanding and enhancing eco-efficiency in the production of drinking water, it is not without limitations, which also highlight opportunities for future research. First, the eco-efficiency assessment in this study is static, meaning it does not account for temporal variations in drinking water

Table 5
Eco-efficiency and savings based on catch basin.

Unitary process	Presence	Number of DWTPs	Average Eco-efficiency	Average cost savings (US$/$m^3$)	Average GHG savings (gCO_{2eq}/m^3)
Catch-basin	No	28	0.655	0.011	16.117
	Yes	8	0.387	0.009	8.461
Coagulation-flocculation	No	12	0.716	0.006	16.626
	Yes	24	0.535	0.013	13.310

volume and quality or seasonal energy use. Expanding the analysis to include time-series data would offer valuable insights into the temporal dynamics of DWTP eco-efficiency. Second, the study focuses on Scope 2 GHG emissions, excluding Scope 1 and 3 emissions, which may lead to an underestimation of the total environmental impact associated with drinking water production. Future research could integrate Scope 1 and 3 emissions to provide a more comprehensive assessment of carbon emissions across the entire value chain. Finally, the case study is limited to a sample of Chilean DWTPs, constrained by data availability. Conducting comparative studies across different countries would help to identify how variations in operational practices and regulatory frameworks influence the eco-efficiency of DWTPs, offering valuable insights for water regulators and policymakers.

CRediT authorship contribution statement

Ramon Sala-Garrido: Writing – review & editing, Methodology, Data curation. **Alexandros Maziotis:** Writing – original draft, Formal analysis, Data curation, Conceptualization. **Maria Molinos-Senante:** Writing – original draft, Project administration, Formal analysis, Conceptualization.

Declaration of competing interest

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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Data availability

Data will be made available on request.

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Further reading

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