Sustainable Cities and Society 85 (2022) 104091

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Estimating the cost efficiency and marginal cost of carbon reductions in the production of drinking water

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ARTICLE INFO

Keywords:
Greenhouse gas emissions
Drinking water treatment
Performance
Stochastic frontier analysis
Environmental variables
Water industry

ABSTRACT

Access to safe, reliable and affordable drinking water is a human right that should be achieved without neglecting Sustainable Development Goal 13 of the United Nations related to climate action. The production of drinking water involves using a non-negligible amount of energy, leading to relevant economic costs and greenhouse gas (GHG) emissions. Here, we employed a parametric method to assess the cost efficiency of a sample of drinking water treatment plants (DWTPs) and to estimate the marginal cost of reducing GHG emissions. The average cost efficiency was 0.386, indicating that the evaluated DWTPs had notable room (61.4%) to save costs. The average marginal cost was estimated at 30€ per ton of CO_{2eq}. When comparing this value with the current carbon costs of carbon trading systems, reducing the GHG emissions of DWTPs might be cost-effective. The parametric approach enabled us to evaluate the influence of several environmental variables on the cost efficiency and marginal cost of reducing GHG emissions. Specifically, the size of the facility and source of raw water significantly influenced DWTP performance. In conclusion, this study provides a novel tool to obtain insights on the water-energy nexus for informed decisions towards a more sustainable urban water cycle.

1. Introduction

Access to safe, affordable and reliable drinking water service is a basic human right (UN, 2010). However, two billion people (26%) still lack safely managed drinking water. Hence, Goal 6 of the Sustainable Development Goals (SDGs) by the United Nations sought to achieve universal and equitable access to safe and affordable drinking water for all (UN, 2015). However, the abstraction, treatment and distribution of water are energy intensive activities (Facchini et al., 2017; Molinos-Senante & Sala-Garrido, 2018; Qiu et al., 2022). Any use of energy significantly increases the carbon footprint of the urban water cycle and operational costs of water utilities (Leveque et al., 2021; Zhang et al., 2021). For example, electricity use accounts for approximately 80% of drinking water processing and distribution costs (NYSERDA, 2008). Zib et al. (2021) assessed the carbon footprints of operational energy use for 76 wastewater treatment plants and 64 drinking water treatment plants (DWTPs) across the United States (US). The greenhouse gas (GHG) emissions associated with electricity, natural gas, and fuel oil consumption of them were estimated to be 26.5×10^9 and 16.2×10^9 Kg CO_{2eq}/year, respectively, which is equivalent to 2.1% of total emissions from the US electrical sector each year. In this context, Goal 13 of the SDG focused on climate action. In particular, target 13.2 seeks to integrate climate change measures into national policies, strategies and planning (UN, 2015). As evidenced in the review conducted by Chini et al. (2020), synergistic approaches, in terms of economic and environmental performance, are vital for helping decision makers (water regulators and water utilities) to improve sustainability in the provision of drinking water.

Several studies (e.g., Chen et al., 2018; Gerbens-Leenes, 2016; Liao et al., 2020; Wakeel et al., 2016; Zaman et al., 2021) have explored the link between energy use and GHG emissions in the urban water cycle at city and national levels. These studies argued that, in the future, more energy will be required to deliver drinking water services to more people, which will impact on the economic performance and carbon emissions of water treatment facilities. Other studies focused on evaluating the intensity of energy use by DWTPs (e.g., Lam et al., 2017;

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https://doi.org/10.1016/j.scs.2022.104091
Received 23 March 2022; Received in revised form 29 June 2022; Accepted 23 July 2022
Available online 25 July 2022
2210-6707/

Loubet et al., 2014; Molinos-Senante & Sala-Garrido 2017). However, as Molinos-Senante and Sala-Garrido (2018) demonstrated, energy intensity and energy efficiency are different concepts,[1] with efficiency being a more reliable metric for benchmarking purposes. Within the last 5 years, several studies assessed the environmental performance of DWTPs, with a focus on energy consumption (Ananda, 2019; Molinos-Senante & Sala-Garrido, 2018, 2019; Rodríguez-Merchan et al., 2021; Sala-Garrido & Molinos-Senante, 2020). Despite the relevance of past research in formulating the framework of the water-energy nexus, limitations exist. First, these studies focused on assessing the energy efficiency of DWTPs using non-parametric techniques, such as Data Envelopment Analysis (DEA), which do not allow noise to be incorporated in the analysis. Consequently, any deviations from the efficient frontier were attributed to efficiency only (Coelli et al., 2005), which might lead to biased results (Koengkan et al., 2022). Second, environmental variables or operational characteristics of DWTPs (such as the source of raw water, size of the facility or its age) were not considered in estimates of efficiency. Overlooking the effect of environmental variables on performance might have notable consequences when generating efficiency scores for benchmarking purposes (Song et al., 2018). Third, these studies did not investigate the potential relationship between the efficiency of DWTPs and marginal cost of reducing GHG emissions. To the best of our knowledge, only Molinos-Senante and Guzman (2018) estimated a shadow price for reducing carbon emissions during the water treatment process. However, these authors used non-parametric techniques to derive their estimates, leading to the limitations identified here.

Thus, here, we employed a parametric method to assess the cost efficiency of a sample of drinking water treatment plants (DWTPs) and to estimate the marginal cost of reducing GHG emissions. The objectives were to: (1) quantify the cost efficiency of a sample of DWTPs using parametric techniques; (2) estimate the marginal cost of reducing GHG emissions when treating raw water, and (3) use clustering techniques to improve our understanding on the relationships among cost efficiency, marginal cost of reducing GHG emissions and operational characteristics of DWTPs. To the best of our knowledge, this is a pioneering approach because it integrates a set of environmental variables to estimate the efficiency and cost of reducing GHG emissions in an energy intensive process of the urban water cycle (i.e. drinking water treatment process). Moreover, there are no published studies that assessed the economic and environmental cost involved in reducing carbon emissions in DWTPs. Our results present a novel approach that overcomes the limitations of existing studies, and contributes to understand the water-energy nexus.

The paper unfolds as follows. Section 2 presents the methodology used, followed by a presentation of the data used in this study in Section 3. Section 4 presents and discusses the main findings of our study, while Section 5 presents our conclusions.

2. Methodology

We used parametric techniques, including Stochastic Frontier Analysis (SFA), to measure the cost efficiency of the drinking water process. We used this approach because it allows us to incorporate both noise and inefficiency. A cost frontier model was used, following Aigner et al. (1977) and Meeusen and van den Broeck (1977), with the form:

$$C_i = f(y_i, w_i; \alpha) + \nu_i + u_i \tag{1}$$

where i denotes the DWTP and C is the cost of running the business. Costs are affected by the generation of a set of outputs, y_i and input prices, w_i. In Eq. (1), f denotes a function (e.g., Cobb-Douglas, translog), and α is the parameter to be estimated. ν_i presents noise, which is distributed following the normal distribution, $\nu_i \sim N(0, \sigma_v^2)$. u_i is inefficiency, which follows the half-normal distribution, $u_i \sim N^+(0, \sigma_u^2)$. The cost efficiency of each DWTP was derived as (Coelli et al., 2005):

$$CE_i = \exp(-u_i) \tag{2}$$

To generate an estimated cost frontier model, we must specify a form for the cost function. A Cobb-Douglas cost function was employed because the sample was small (36 DWTPs) and it does not require many degrees of freedom (Ferro & Mercadier, 2016). When resource prices were lacking, the following cost frontier model was estimated (Jamasb et al., 2012; Maziotis et al., 2021; Molinos-Senante et al., 2021; Mydland et al., 2019):

$$lnC_i = a_0 + \sum_{m=1}^{M} \alpha_m lny_{i,m} + \sum_{q=1}^{q} a_q lnq_{i,q} + \sum_{n=1}^{n} a_n ln\omega_{i,n} + \nu_i + u_i \tag{3}$$

where ln presents logarithms, a_o is the constant term, and ν_i and u_i are noise and inefficiency, respectively. The cost for each DWTP i, C_i, is the dependent variable and m is the total number of outputs that are produced, such as the volume of drinking water delivered. To estimate the marginal cost of reducing undesirable outputs (such as GHG emissions), we also included another cost driver in Eq. (3), q_i. Additional environmental (operating) characteristics might exist that influence the performance of treatment plants, such as ownership and type of water source (see Section 3 for details). The impact of environmental variables on cost efficiency was captured by the term ω_i.

After estimating the cost frontier model in Eq. (3), the marginal cost of reducing GHG for each DWTP i was calculated as:

$$MC_i = -ELC_i \times \frac{C_i}{q_i} \tag{4}$$

where ELC_i presents the elasticity of cost with respect to the cost driver q_i, which was GHG emissions here. In other words, it is the coefficient of GHG emissions estimated from Eq. (3). As before, C_i and q_i denote the costs of running the DWTP and GHG emissions, respectively. These three terms can be used to derive the marginal cost of reducing GHG emissions for each treatment plant, MC_i. This cost also provides a measure of improving service quality and enhancing sustainability. We note that a negative sign is applied to the marginal cost of reducing greenhouse gas emissions because GHG is an inverse measure of quality (Jamasb et al., 2012). We expect to find a negative coefficient for the elasticity of cost with respect to GHG because this means that reducing GHG should be costly overall. Equivalently, improving quality of service increases overall cost. Consequently, the marginal cost of reducing GHG would be positive which is consistent with microeconomic theory.

Cluster analysis was used to quantify how the marginal costs of reducing GHG emissions is associated with cost efficiency and other operating characteristics of DWTPs. The k-means clustering technique was used, following existing studies (e.g., Bonjec & Lattruffe 2007; Cinaroglou, 2020; Lo Storto, 2018; Omrani et al., 2018; Sikka et al., 2009). We first denoted the number of clusters (groups) k, with initial centroids being chosen at random (Tang et al., 2019). Second, each unit was assigned to its closest centroid (Park & Jun, 2009). Finally, the k-means algorithm was stopped when there were no more modifications in the allocation of units among the groups (Bayaraa et al., 2019). The optimal number of clusters was determined using a statistic called silhouette, with values ranging between 0 and 1 (Cinarolglou, 2020). The highest silhouette score provided the optimal number of groups when using the k-means clustering technique (Rousseeuw, 1987).

[1] Energy intensity is defined as the energy consumed (kWh) per unit volume (m^3) of drinking water produced. Hence, this metric does not consider the quality of the raw water, which could have a marked effect on the energy input of DWTPs (Mo et al., 2014). By contrast, energy efficiency is a synthetic index that integrates both the pollutants removed from raw water and the energy used for it. Hence, this metric allows the energy performance of DWTPs to be compared (Molinos-Senante & Sala-Garrido, 2018).

3. Case study

The method developed here was applied empirically to 36 DWTPs in Chile in 2014. The DWTPs were located throughout the country, and had different operating characteristics. For instance, some DWTPs treat surface water, while others treat groundwater. In the econometric specification of Eq. (3), dependent and the explanatory variables were selected based on available data and literature reviews (e.g. Berg & Marques 2011; Goh & See 2021; Molinos-Senante & Guzman 2018; Molinos-Senante & Sala-Garrido 2019). The dependent variable was defined as the annual cost of operating and maintaining DWTPs, which was measured in Chilean pesos per year.[2] Unfortunately, only annual costs were available which did not allow us to conduct a more detailed analysis at daily or monthly scale. The output was the quality-adjusted volume of drinking water produced in m^3/year. The Chilean national regulator reports a synthetic indicator to measure the quality of treated water. This indicator is estimated by considering different quality parameters, such as bacteriology, turbidity, and free residual chlorine (Molinos-Senante & Guzman, 2018). The synthetic indicator takes a value between 0 and 1, with 1 representing drinking water that has passed all tests for quality parameters. To estimate the quality-adjusted output, we multiplied this synthetic indicator with the volume of drinking water produced. GHG emissions were considered as an additional driver. There are indirect GHG emissions measured in kg of CO_2 equivalent (CO_{2eq}) per year. Following Molinos-Senante and Guzman (2018), the GHG emissions from electricity generation required for DWTPs operation were calculated by multiplying the annual electricity used by each facility (MWh/year) with GHG intensity, expressed in tons of CO_{2eq} per MWh of electricity generated. According to the Chilean Ministry of Energy (2018), the production of electricity in Chile in 2014 was based on petroleum (32.3%), carbon (25.2%), biomass (23.1%), natural gas (12.4%), hydroelectricity (6.3%) and other renewable sources (0.7%). Based on this energetic matrix, the GHG emission factor was estimated to be 0.3636 tCO_{2eq}/MWh (CNE, 2014). Because operational costs of DWTPs were available only at annual scale, the GHG emission factor estimated is the annual weighted average for the National Electrical System. Chile has three electrical systems: (i) National Electrical System; (ii) Aysen System and; (iii) Magallanes System. The Aysen and Magallanes systems just operate in the austral zone of the country whereas the National Electrical System covers 3100 kms which is almost the full country. The National Electrical System connects power plants and other electricity generation systems, transmission and distribution companies and therefore the GHG emission factor is the same for the whole system. It should be noted that the 36 DWTPs evaluated in this study are connected to the National Electrical System. It should be noted that in addition to electricity use, the operation of DWTPs involves additional GHG emissions mainly due to the manufacturing and transport of chemicals used to treat water (Biswas & Yek, 2016; Racoviceanu et al., 2007) which, due to data unavailability of Chilean DWTPs, were not considered in this study.

The econometric model employed in this study included additional operating characteristics that could influence the economic and environmental performance of DWTPs. The first variable was the size of the DWTP. Considering the different sizes of the facilities evaluated, DWTPs were classified into four groups based on the water treated: (i) 500,000 m^3/year and 1000,000 m^3/year; (ii) 1000,000 m^3/year and 10,000,000 m^3/year; (iii) 10,000,000 m^3/year and 100,000,000 m^3/year, and (iv) >100,000,000 m^3/year. The second environmental variable captured the age of treatment facility (i.e., the year it was built). In the sample evaluated, the oldest DWTP was built in 1945, and the newest in 2004. Most plants were built after 1990, when the Chilean water industry was privatised. As the assessed DWTPs belong to different water companies, a categorical variable that grouped treatment facilities based on the water company that operates them was included. This variable allowed us to evaluate the impact of management on DWTP efficiency. Moreover, as facilities treat water from different sources, we included a variable that captured the type of raw water that is treated (i.e. surface water versus groundwater).

Table 1 presents a summary of the descriptive statistics of the variables used in the study. The data were provided by the national water regulator, Superintendencia de Servicios Sanitarios (SISS), which monitors the financial and environmental performance of water production process in Chile.

4. Results and discussion

4.1. Estimation of the cost frontier

To estimate energy efficiency of DWTPs, the stochastic cost frontier was estimated (Table 2 presents the coefficients). The elasticity of cost, with respect to output, was positive and statistically significant from zero. As expected, when the volume of drinking water treated increased, the operating costs also increased. Specifically, a 1% increase in the volumes of quality adjusted water could increase operating costs by 0.716%, on average. The estimated coefficient of GHG emissions was negative, indicating a positive marginal cost. Thus, reducing the level of GHG emissions during the water treatment process could eventually lead to higher levels of efficiency (Jamasb et al., 2012). The low magnitude of the elasticity in cost with respect to GHG showed that reducing carbon emissions might not be costly. Thus, good environmental and economic performance could be achieved at the same time.

Except for water company management, all other environmental variables had a statistically significant impact on DWTP costs (Table 2). Facility size had a positive impact on company costs. Thus, facilities that treat high volumes of water could incur higher economic costs. The more water that is treated, the higher the treatment costs, which might lead to higher levels of carbon emissions and inefficiency. Thus, large-sized treatment plants might be less eco-efficient than smaller ones. In other words, on average, the evaluated DWTPs present diseconomies of scale. It involves that the operating costs of the DWTPs increase as the volume of drinking water produced increases. There might be different causes of diseconomies of scale such as the complexity of the operation, method of production, lack of efficient communication between employees. Usually, large DWTPs are more difficult to operate and therefore, require specific expertise which is more expensive. Hence, a potential action to be implemented by the Chilean water industry is to increase the number of small-sized DWTPs. This action would generate both economic and resilience benefits (Torre et al., 2021). Evidence on the presence of economies in water facilities is mixed (Berg & Marques, 2011; Carvalho et al., 2012; Hernández-Chover et al., 2018).

The estimated coefficient of variable age was positive. Thus, treatment facilities that were built recently might be characterised by higher operating costs compared to older ones. However, age did not impact costs and inefficiency, as shown by the magnitude of the estimated coefficient. The type of raw water source negatively affected DWTP costs. Water taken from groundwater is associated with lower operating costs and inefficiency compared to water taken from the surface. This difference might be attributed to the treatment costs required to clean water from groundwater sources being lower than that from surface sources. Finally, the statistically significance of σ_u^2 justified the use of a stochastic cost frontier model.

4.2. Estimate of cost efficiency and marginal cost of reducing GHG emissions

Fig. 1 presents the cost efficiency scores for each DWTP. First, it is found that substantial cost inefficiency exists among the Chilean DWTPs.

[2] To express operational costs is euros, the following conversion rate was applied: 855 CLP ≅ 1 €

Table 1
Descriptive statistics of the variables employed.

Variables	Unit of measurement	Mean	Standard Deviation	Minimum	Maximum
Operational costs	10^3 €/year	210,022.62	346,295.28	54.84	1,559,241.68
Quality adjusted volume of water	10^3 m^3/year	17,155,555.61	59,638,214.84	30,624.36	344,633,664.28
Greenhouse gas emissions	kg CO_{2eq}/year	109,004.08	165,263.22	2986.30	806,782.04

Observations: 36.

Table 2
Estimated results from the stochastic frontier analysis model.

Variables	Coef.	Std. Err.	Z-stat	*p*-value
Constant	6.836	1.110	**6.159**	0.000
Qual. adj. water delivered	0.716	0.349	**2.051**	0.040
Greenhouse gasses	−0.012	0.005	**−2.530**	0.011
Size	0.408	0.139	**2.935**	0.000
Age	0.002	0.001	***1.653***	0.098
Company management	−0.168	0.135	−1.239	0.215
Water source	−1.711	0.097	**−17.714**	0.000
σ_u^2	2.490	0.293	**8.485**	0.000
σ_v^2	0.190	0.069	**2.773**	0.005
λ	13.105	0.193	**67.744**	0.000
Log-likelihood	−58.93			
Obs	36			

Dependent variable is operating costs.
Bold indicates that coefficients are statistically significant at 5% significance level.
Bold italic indicates that coefficients are statistically significant at 10% significance level.

The average cost efficiency was 0.3862, indicating that the potential savings in costs could reach of 61.38%. Thus, several DWTPs need to make substantial improvements to their managerial practices to become more eco-efficient. For instance, DWTPs could use energy from renewable resources during the treatment process. This could lower their energy and operating costs, leading to lower carbon emissions and improved economic and environmental efficiency (Sala-Garrido et al., 2021). Only six out of 36 DWTPs (16.7%) were fully efficient (i.e., reported an efficiency score of 1). These facilities were considered as the best in terms of its performance. Furthermore, four out of 36 DWTPs reported an efficiency score >0.5. The rest of the DWTPs (26 out of 36 facilities; 72.2%) reported a cost efficiency score <0.5. These facilities could save more than 50% of current operational costs if they performed similar to the best DWTPs.

Almost half of the DWTPs (17 out of 36) reported an efficiency score which ranged from 0.016 to 0.200. This group of DWTPs need to improve their costs by up to 80% to catch up with the most efficient facilities. Slightly higher cost efficiency scores were reported for the other DWTPs. However, these facilities also need improve performance, due to considerable cost inefficiency existing. For instance, seven of the

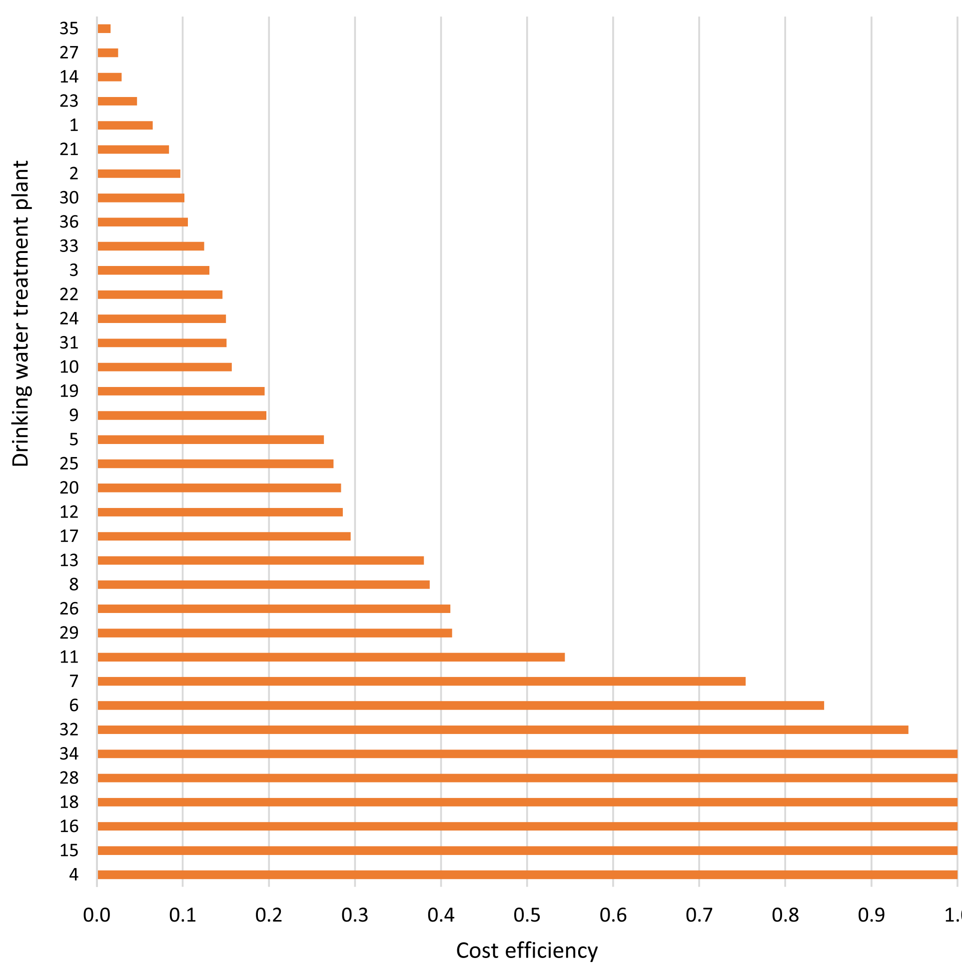

Fig. 1. Cost efficiency of Chilean drinking water treatment plants evaluated.

36 DWTPs reported an efficiency of 0.21–0.40, while it was 0.41–0.60 for just three facilities. The potential cost savings among these treatment facilities could range from 40% to 79% for the same level of output. Some basic actions that DWTPs could adopt to improve efficiency from an energetic perspective include: (i) installing smart meters in different unitary processes of the facility (Longo et al., 2016); (ii) implementing control systems for the optimal operation of water pumps; and iii) supplying energy efficient ballasts for plant fluorescent fixtures and ultraviolet disinfection or pretreatment systems (EPA, 2013).

On average, the marginal cost of reducing GHG emissions was 30.87€/ton (Fig. 2). Thus, on average, Chilean treatment facilities would need to spend an extra 30.87€ in operating expenditure to prevent 1 ton of CO_{2eq} emissions. Alternatively, the release of 1 additional ton of CO_{2eq} emissions to the atmosphere incurs an environmental cost of 30.87€. This finding is consistent with that reported by Molinos-Senante and Guzman (2018), with an average marginal abatement cost of 40€/ton CO_{2eq}. These authors used non-parametric techniques to estimate the shadow price of reducing carbon emissions at several treatment plants in Chile. Unlike our study, the authors did not include any environmental variables in their efficiency analysis. Focusing on the European Union Emission Trading System (EU ETS), carbon prices were highly variable over the last five years, with a minimum value <5 €/ton CO_{2eq}. Nevertheless, carbon prices have risen, reaching 96.8 €/ton CO_{2eq} in February 2022, which is the highest price since the carbon market launched in 2005.

To illustrate the variability of the marginal cost of reducing GHG emissions, Fig. 3 shows the marginal cost estimated for each DWTP against GHG emissions per cubic meter of treated water. It is shown that the marginal cost of reducing GHG emissions ranged from 0.02 to 198.88€/ton CO_{2eq} whereas the emissions of GHG varied between 0.0017 and 0.261 Kg CO_{2eq}/m^3 (Fig. 3). It is observed that the largest marginal costs of reducing GHG emissions correspond to DWTPs whose GHG emissions are the lowest. The fourteen facilities (Fig. 2) whose marginal cost of reducing GHG emissions is larger than 20 Euro/ton CO_{2eq} present emissions of GHG lower than 0.02 Kg CO_{2eq}/m^3. By contrast, the two DWTPs whose marginal cost of reducing GHG emissions is the lowest (0.16 and 0.02 Euro/ton CO_{2eq}) emit much more CO_{2eq} to produce drinking water (0.208 and 0.233 Kg CO_{2eq}/m^3). In other words, it is evidenced that those DWTPs which have already done efforts to reduce GHG emissions to produce drinking water, present large marginal cost to reduce carbon emissions because they have already implemented the most cost-effective measures to reduce energy consumption and therefore, GHG emissions. By contrast, as expected, those facilities with large GHG emissions could adopt relatively cheap actions and technologies to reduce their carbon footprint and therefore, its marginal costs of reducing GHG emissions are comparatively low.

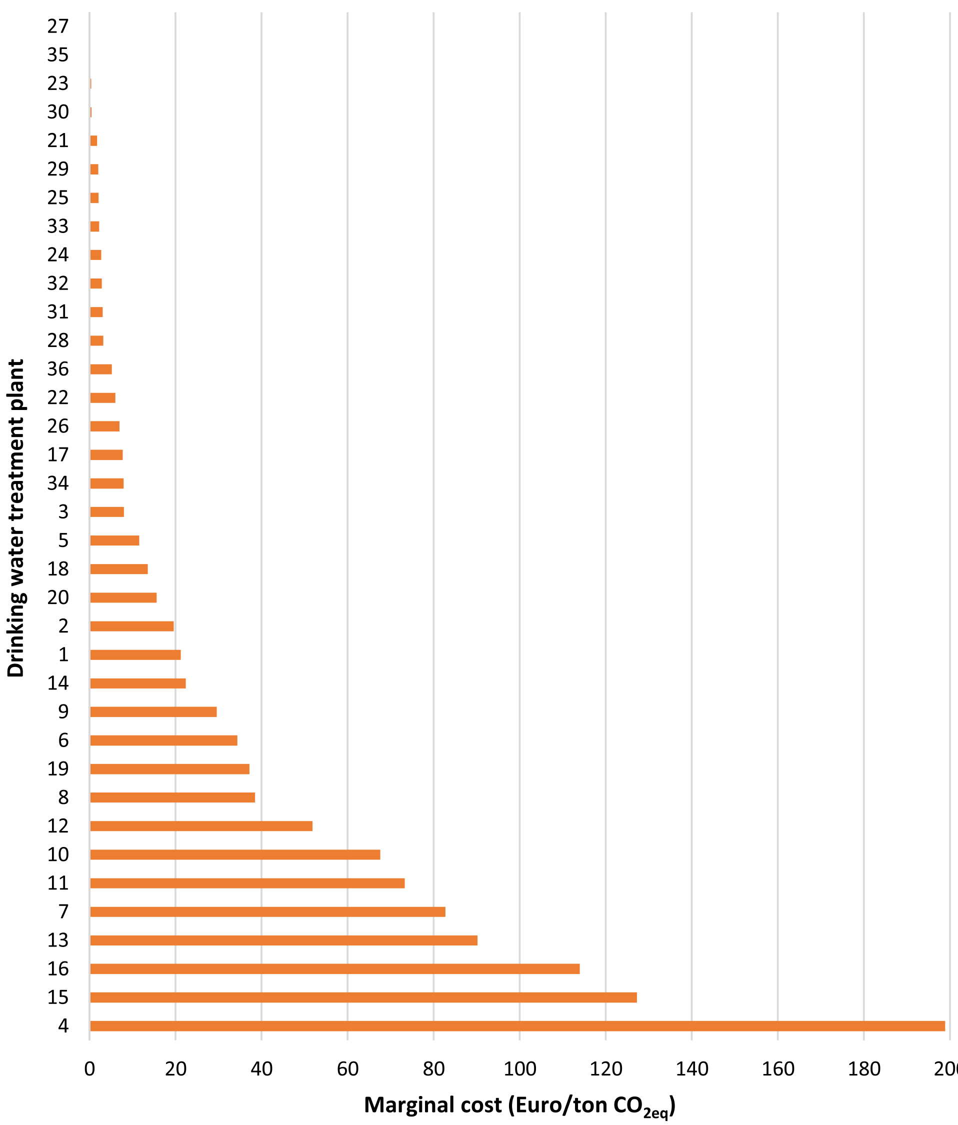

Fig. 2. Marginal cost of reducing greenhouse gas emissions in Chilean drinking water treatment plants.

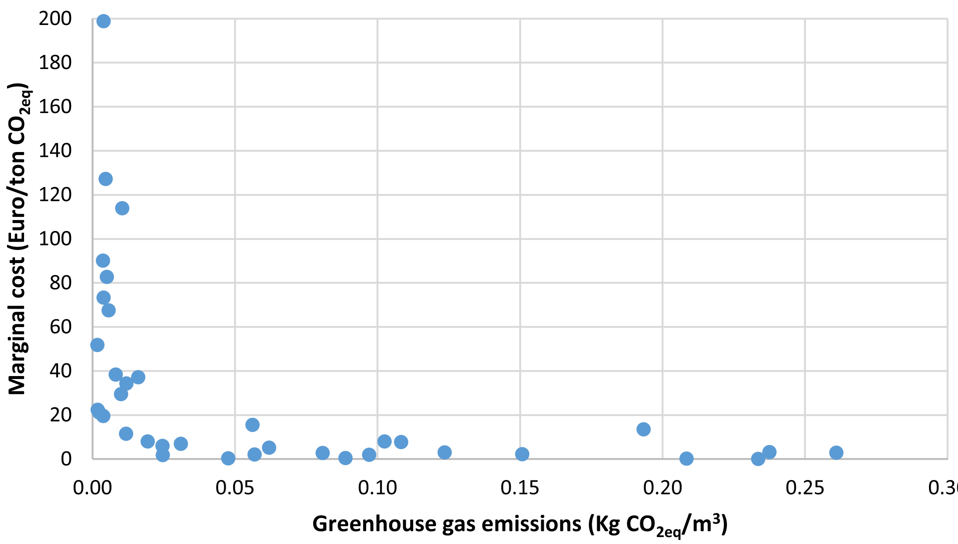

Fig. 3. Relationship between marginal cost of reducing greenhouse gas emissions and the emission of greenhouse gasses in Chilean drinking water treatment plants.

When comparing cost efficiency scores and the marginal cost of reducing GHG emissions (Figs. 1 and 2), some higher costs of reducing carbon emissions were reported for some DWTPs, despite high efficiency levels. Consequently, for this group of facilities, improvements in environmental performance incurred a cost. Improvements in environmental efficiency could be achieved by adopting new energy efficient technologies leading to lower levels of carbon emissions during the treatment process. For fully efficient DWTPs, the marginal cost of reducing CO_{2eq} ranged between 3.21€/ton and 198.88€/ton. For these facilities, the cost of reducing 1 ton of CO_{2eq} emissions from the water treatment process could be up to 198.88€. For three of the six fully efficient DWTPs, avoiding 1 ton of CO_{2eq} emissions was associated with extra operating expenditure, which could reach range between 113.93 and 198.88€. For the remaining fully efficient treatment plants, the costs of reducing carbon emissions was considerably lower.

DWTPs were classified into two groups by the clustering analysis of silhouette scores based on their cost efficiency scores and the marginal cost of reducing GHG emissions (Table 3; see supplementary material for details). We also summarised the operating characteristics of the DWTPs to identify what could impact their performance.

The first group included DWTPs that treat large volumes of water and release high levels of carbon emissions to the atmosphere. The average cost efficiency was 0.199, meaning that these facilities could reduce production costs by 80% on average to generate the same level of output. These large facilities reported an average marginal cost of 20 €/tons for reducing GHG emissions. Thus, large facilities could increase operating expenditure by 20€ to prevent 1 ton of carbon emissions from the treatment of raw water. Ultimately, large facilities could improve performance by investing in new carbon emission reducing technologies, while improving the services to the end-user customers.

The second group included small-sized facilities that treat lower volumes of water and, consequently, have lower GHG emissions. As it was illustrated on Table 2, these facilities were characterized by lower operating and maintenance costs compared to larger facilities. Small DWTPs had an average cost efficiency of 0.949, with the potential for 5% cost savings. The extra spend required in operating expenditure to avoid 1 ton of CO_{2eq} could be 65€. Thus, small DWTPs could improve performance by reducing overall production costs. For instance, the use of energy from renewable sources could lead to lower energy costs and operating costs.

Both clusters displayed similar characteristics for their operating factors. For instance, on average, both large and small DWTPs were built recently (1990 and 1991). On average, these DWTPs treat water from groundwater sources, and the amount of water that is treated usually ranges between 500,000 to 1000,000 *m*<sup>3<sup>*s* per year. Finally, large treatment plants are managed by six water companies, whereas smaller ones were operated by five water companies.

4.3. Influence of operational characteristics on the cost efficiency and marginal cost of reducing GHG emissions

We then evaluated how the cost efficiency results and marginal cost of reducing carbon emissions were distributed across DWTPs based on each operating characteristic. This approach allowed us to understand the relationship between the performance of DWTPs and the environment in which they operate. DWTPs that treat more than 10 million m^3/year were characterised by low levels of efficiency (Table 4). For this group, the extra spend in operating expenditure to avoid 1 ton of carbon

Table 4
Average cost efficiency, marginal cost of reducing GHG and GHG emissions based on the size of DWTPs.

Size of drinking water treatment plant (m^3/year)	Number of DWTPs	Cost efficiency	MC of reducing GHG (€/ton)	GHG emissions (Kg CO_{2eq}/m^3)
[0 – 500,000)	11	0.264	6.2	0.119
[500,000–1000,000)	7	0.579	22.4	0.087
[1000,000–10,000,000)	11	0.452	53.3	0.035
[10,000,000-100,000,000)	5	0.362	51.9	0.006
[> 100,000,000	2	0.081	20.4	0.003

Table 3
Summary of cluster analysis of Chilean DWTPs.

Clusters	Cost efficiency	Marginal cost reducing CO_{2eq} (€/ton)	Operating costs (10^3 €/year)	Quality adjusted volumes of water (10^3 m^3/year)	GHG(kg CO_{2eq}/year)	Year built
1	0.199	20	2644,810	21,371,576	115,968	1991
2	0.949	65	346,647	4507,490	88,110	1990

emissions during the treatment process was 36.1€. By contrast, smaller treatment plants reported higher levels of efficiency. For instance, DWTPs treating between 500,000 and 1 million cubic metres per year reported an average efficiency score of 0.579. However, considerable improvements in the managerial practices of DWTPs are required to increase efficiency. A positive correlation between the volume of treated water and cost of reducing GHG emissions was observed. The more water that is treated, the higher the cost to reduce carbon emissions. This correlation was exhausted in high volumes of water, which exceeded the 100 million cubic metres per year. Table 4 also evidences that as the size of the DWTPs increases, the emissions of GHG per cubic meter of drinking water produced decreases. This pattern is associated with the presence of economies of scale in energy consumption for the production of drinking water. Similar findings were evidenced by Molinos-Senante and Maziotis (2022) who estimated the energy efficiency of a sample of 146 DWTPs.To evaluate whether differences in cost efficiency scores marginal costs of reducing GHG emissions and GHG emissions per cubic meter of drinking water produced were significant statistically, Kruskal-Wallis tests were conducted. For the three variables, p-values were below 0.05, confirming that cost efficiency, the marginal cost of reducing GHG emissions and GHG emissions per cubic meter of drinking water produced were influenced by the size of DWTPs.

The second variable analysed was the age of DWTPs. Based on the year of construction, treatment facilities were classified into three groups: (i) before 1990; (ii) during the 1990–2000 period, and (iii) after 2000. These groupings were selected because, before 1990, the Chilean water industry was under public ownership, whereas a relevant number of water companies were privatised during 1990–2000. DWTPs built between before 1990 and during 1990–2000 appeared to be slightly more efficient than those built after 2000 (Table 5). However, based on the Kruskal–Wallis, we did not reject the hypothesis of equality of means for cost efficiency scores with 95% significance. In other words, the age of the facilities did not significantly influence economic performance. The cost of reducing carbon emissions was smaller for DWTPs built under private ownership. This phenomenon might be attributed to newer plants having lower carbon emissions compared to older ones due to newer technologies. However, differences among the three groups of DWTPs were not statistically significant.

Most of the evaluated Chilean DWTPs treated water from groundwater sources (Table 6). By contrast, only 9 facilities treat surface water which is from rivers. The average cost efficiency of this group of DWTPs was 0.429, whereas that of facilities treating water from surface sources was 0.259 on average. Notable differences were also revealed in terms of the marginal cost of reducing GHG emissions. DWTPs treating surface water reported an opportunity cost of 17€/ton CO_{2eq} for carbon emissions. In contrast, higher marginal costs (36€/ton CO_{2eq}) were reported for plants treating water from groundwater sources. Table 6 evidences that GHG emissions per cubic meter of drinking water produced are larger for those DWTPs that treat surface water than for those facilities treating groundwater. This is mainly because surface water is mostly treated to remove turbidity involving a noticeable use of energy. By contrast, groundwater present lower concentration of pollutants and therefore, less energy is required to produce drinking water (Pastén et al., 2021). The Kruskal–Wallis test indicated that differences in the efficiency and marginal costs for the two groups of DWTPs were statistically significant.

Table 5
Average cost efficiency, marginal cost of reducing GHG and GHG emissions based on the age of DWTPs.

Year of built of drinking water treatment plants	Number of DWTPs	Cost efficiency	MC of reducing GHG (€/ton)	GHG emissions (Kg CO_{2eq}/m^3)
Before 1990	10	0.390	51.0	0.008
Between 1990 and 2000	14	0.389	40.0	0.063
After 2000	12	0.381	13.0	0.137

Table 6
Average cost efficiency, marginal cost of reducing GHG and GHG emissions based on the source of raw water.

Source of raw water	Number of DWTPs	Cost efficiency	MC of reducing GHG (€/ton)	GHG emissions (Kg CO_{2eq}/m^3)
Surface water (river)	9	0.259	17.0	0.103
Groundwater	27	0.429	36.0	0.051

5. Conclusions

Moving towards a more sustainable urban water cycle is a relevant challenge for water companies, which should aim improve their economic efficiency and reduce GHG emissions. In this study, we evaluated the cost efficiency and marginal costs of reducing GHG emissions for a sample of DWTPs in Chile. Because, these facilities operate under different environmental conditions, we also investigated the influence of these conditions on the performance of water treatment facilities.

On average, the Chilean DWTPs had a cost efficiency of 0.386, with the potential for savings in costs of 61.4%, on average. Only six of the 36 DWTPs were efficient (i.e. constituting best practice facilities). Thus, substantial improvements are required in the water treatment process. The marginal cost of reducing carbon emissions was 30 €/ton of CO_{2eq}. Thus, on average, DWTPs need to spend an extra 30€ in operating expenditure to prevent 1 ton of carbon emissions released from water treatment. This figure is considerably lower than the current carbon costs of the EU ETS; thus, DWTPs could adopt new technological practices to improve environmental performance. In particular, facility size and raw water source significantly influence the cost efficiency of DWTPs and the marginal costs of reducing GHG emissions. However, there was no substantial difference in the efficiency of DWTPs that were constructed before and after privatization.

From a policy perspective, this study developed a novel approach for assessing the economic and environmental performance of water treatment processing. It provides policy makers with an opportunity to determine how efficient treatment facilities are and what drives production costs. Managers could gain new insights on what factors affect operational costs, such as the size of treatment plant or source of treated water (e.g. groundwater versus surface resources). Moreover, our empirical approach provides a way of estimating the costs required to reduce carbon emissions when treating water, which is an energy intensive activity. This information could be used by managers to determine whether the cost of reducing carbon emissions is costly, and adopt practices that could reduce energy and other costs of treating water. Acquiring this information of great importance to move towards an energy efficient and sustainable urban water cycle, with huge benefits for the environment and people's health and well-being.

Because data for operational costs of DWTPs was available only at annual scale, the marginal cost of reducing GHG emissions estimated in this study is the annual average. It should be noted that operational costs of DWTPs and GHG emission factors are not constant over time, but relevant changes occur throughout the year. This is a limitation of this study and therefore, future research studies, if data is available, might focus on assessing the dynamics of the marginal cost of reducing GHG emissions from the production of drinking water. This study just considers indirect GHG emissions, i.e., those generated during the production of the electricity consumed by the DWTPs. Nevertheless, the production and use of chemicals needed to produce drinking water also contributes to GHG emissions and therefore, they could be considered in future research to estimate the marginal costs of reducing carbon emissions from DWTPs.

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.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2022.104091.

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