A COMPRENHESIVE ECO-EFFICIENCY ANALYSIS OF WASTEWATER TREATMENT PLANTS: ESTIMATION OF OPTIMAL OPERATIONAL COSTS AND GREENHOUSE GAS EMISSIONS

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A B S T R A C T

The transition to a neutral carbon and sustainable urban water cycle requires improving eco-efficiency in wastewater treatment processes. To support decision-making based on eco-efficiency evaluations, reliable estimations are fundamental. In this study, the eco-efficiency of a sample of 109 WWTPs was evaluated using efficiency analysis tree method. It combines machine learning and linear programming techniques and therefore, overcomes overfitting limitations of non-parametric methods used by past research on this topic. Results from the case study revealed that optimal costs and greenhouse gas emissions depend on the quantity of organic matter and suspended solids removed from wastewater. The estimated average eco-efficiency is 0.373 which involves that the assessed WWTPs could save 0.32 €/m^3 and 0.11 kg of CO_2 equivalent/m^3. Moreover, only 4 out of 109 WWTPs are identified as eco-efficient which implies that the majority of the evaluated facilities can achieve substantial savings in operational costs and greenhouse gas emissions.

1. Introduction

Wastewater treatment is crucial for safeguarding human health and preventing environmental degradation (IOC/UNESCO 2011; Feng et al., 2022). The United Nations' Sustainable Development Goals, established in 2015, emphasize the importance of wastewater treatment in achieving sustainable development (United Nations, 2015). However, it is worth noting that wastewater treatment is typically an energy-intensive process (Yang and Chen, 2021). Studies have shown that in Europe, the collection and treatment of wastewater can account for 1% of global electrical energy consumption (Walker et al., 2021), with wastewater treatment plants (WWTPs) alone contributing to over 20% of the electrical consumption in local authorities (Longo et al., 2016).

Additionally, the energy use in WWTPs is associated with greenhouse gas (GHG) emissions, particularly in regions where non-renewable energy sources are predominant (Huang et al., 2021). Inefficient wastewater treatment processes can result in significant GHG emissions (Hao et al., 2017; Cardoso et al., 2021). The reduction of GHG emissions and the pursuit of carbon neutrality in WWTPs have gained substantial attention from researchers and policymakers since the adoption of the

Paris Agreement at the 21st Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change in 2015 (Xi et al., 2023). Addressing these challenges necessitates improving the operational efficiency and maintenance of WWTPs to reduce costs and enhance environmental performance. Consequently, the assessment of the economic and environmental efficiency, known as eco-efficiency, of WWTPs becomes essential.

Eco-efficiency was initially defined by Schaltegger and Sturm (1989) as the ratio between value added and environmental impacts. Eco-efficiency assessments provide entities with a better understanding of their activities and impacts (Torregrossa et al., 2018; Ramírez-Melgarejo et al., 2021). In the context of WWTPs, eco-efficiency assessment involves evaluating pollutant removal efficiency, resource consumption, and environmental impacts, such as GHG emissions (Mocholi-Arce et al., 2020). Enhancements in eco-efficiency can result in cost savings, which can be passed on to citizens through lower tariffs, as well as reductions in GHG emissions, contributing to carbon neutrality (Gémar et al., 2018; Liu et al., 2021).

Previous research on the eco-efficiency of WWTPs has been limited in integrating economic costs, pollutant removal efficiency (desirable outputs), and GHG emissions (undesirable outputs). Some studies

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focused solely on indirect GHG emissions associated with the production and transportation of chemicals and electricity consumption at WWTPs (Molinos-Senante et al., 2016; Gémar et al., 2018; Gómez et al., 2018; Mocholi-Arce et al., 2020; Fallahiarezoudar et al., 2022). Others considered both direct and indirect GHG emissions in their assessments (Molinos-Senante et al., 2014; Dong et al., 2017; Ramírez-Melgarejo et al., 2021; Xi et al., 2023). However, all these studies employed the Data Envelopment Analysis (DEA) method to estimate eco-efficiency scores.

DEA is a non-parametric technique that constructs the efficient production frontier using observed data on inputs and outputs through linear programming (Ferreira et al., 2023). While DEA assumes that deviations from the frontier represent inefficiency only, it is sensitive to outliers and can suffer from overfitting issues, leading to biased eco-efficiency scores (Carvalho and Marques, 2016; Guerrini et al., 2016; Esteve et al., 2020; Esteve et al., 2021; Esteve et al., 2022).

To address the overfitting limitation of DEA, Esteve et al. (2020) introduced a novel technique called Efficiency Analysis Tree (EAT), which combines machine learning and linear programming approaches to measure efficiency. The EAT method utilizes regression trees to predict the response variable based on various thresholds of predictor variables. Notably, the EAT method assumes free disposability, enabling the estimation of the maximum levels of operating costs and GHG emissions based on the volume of wastewater treated for pollutant removal. This information provides WWTP managers and regulators with valuable insights into potential economic and environmental improvements in the wastewater treatment process. Maziotis et al. (2023) demonstrated the utility of the EAT approach in measuring carbon efficiency in water utilities in England and Wales. However, to the best of our knowledge, there are no previous studies that have utilized the positive features of the EAT method to evaluate the eco-efficiency of WWTPs. Our study aims to fill this gap in the literature.

The objectives of our study are threefold. Firstly, we aim to assess the eco-efficiency of a sample of WWTPs using the EAT method. Unlike DEA, EAT allows us to quantify the maximum levels of operating expenditure and GHG emissions for different levels of pollutant removal from wastewater. Secondly, we seek to determine the potential savings in operating expenditure and GHG emissions that could be achieved if the evaluated WWTPs were eco-efficient. Our study makes several contributions to the existing literature. Unlike previous studies, we employ a novel methodological approach that combines machine learning, production economics, and non-parametric techniques. Furthermore, we estimate the optimal levels of operational expenditure and GHG emissions for WWTPs for the first time. Our research is conducted on a sample of Spanish WWTPs.

2. Material and methods

2.1. Eco-efficiency assessment

The EAT method is utilized in this study to assess the eco-efficiency of WWTPs which is as follows. Let's presume that a set of predictor factors $x_1, \ldots, x_m$ with $x_i \in R^m$ (i.e., pollutants removed from wastewater) is used to predict a vector of response variables $y, \ldots, y_n$ with $y_i \in R^n$ (i.e., operational costs and GHG emissions). The EAT method picks a predictor x_i and a threshold $s_j \in S_j$ where S_j is the set of likely rules (or thresholds) for j to divide the data into two nodes, t_R and t_L (Esteve et al., 2021, Esteve et al., 2022). The split into these two nodes is carried out using the sum of the mean squared error. The mathematical presentation of the EAT method is as follows:

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

where n is the size of the sample, t presents the nodes of the tree, t_L and t_R are the left and right nodes, respectively, $R(t)$ denotes the mean square

error of each node t, $y(t_L)$ and $y(t_R)$ denote the estimated values of the response variable based on the data in t_L and t_R (Esteve et al., 2020).

With respect to the estimated values of the response variable, they are derived as follows:

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

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

where T is the sub-tree that the EAT approach produces, k is the number of splits, $y(I_{T(k|t^* \to t_L, t_R)}(t_L))$ and $y(I_{T(k|t^* \to t_L, t_R)}(t_R))$ present the leaf nodes of the tree generated after completing the $k - th$ split that Pareto rules node t_L and t_R (Esteve et al., 2020; Esteve et al., 2022).

To deal with overfitting issues, the EAT method employs cross-validation techniques to obtain the best regression tree (Maziotis et al., 2023). Therefore, the production technology that the EAT approach estimates is presented as follows:

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

where $d_{T_k}(x)$ presents the predictor estimator related to the sub-tree T_k.

The estimation of the eco-efficiency for each WWTP is done by solving the following linear programming model:

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

$s.t.$

$$\sum_{t \in T^*} \lambda_t a_j^t \leq x_{jk}, \ j = 1, \ldots, m$$

$$\sum_{t \in T^*} \lambda_t d_{rT^*}^t(a^t) \geq \theta y_{jk}, \ r = 1, \ldots, p$$

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

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

In equation (5), θ^{EAT} is the eco-efficiency score and $a^t, d_{T^*}(a^t)$ capture points in the input–output space for all $t \in T^*$ where $*$ captures the final sub-tree. The λ variables in the constraints are intensity variables that are used to build the eco-efficient frontier. When the eco-efficiency score equals to one ($\theta^{EAT} = 1$), then the WWTP under evaluation is fully eco-efficient. In contrast, if $\theta^{EAT} < 1$, then the WWTP is considered eco-inefficient and therefore, it presents potential room for improvement.

Based on eco-efficiency scores (θ^{EAT}) estimated using Eq. (5), savings on operating costs and GHG emissions are estimated Eqs. 6 and (7):

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

$$GHG_s = GHG_c * (1 - \theta^{EAT}) \quad (7)$$

where $Operating\ costs_s$ are the potential savings in operating costs if the WWTP was fully eco-efficient. Furthermore, $Operating\ costs_c$ are the actual levels of operating costs for each assessed treatment plant. Similarly, GHG_s are the potential savings in GHG emissions that the plant could achieve if it was fully eco-efficient. GHG_c are the actual levels of GHG emissions for each WWTP under evaluation.

2.2. Data and variables selection

In our case study, we focus on evaluating the eco-efficiency of 109 wastewater treatment plants (WWTPs) situated in Catalonia, a region in the northeast of Spain. These WWTPs are responsible for removing suspended solids (SS), organic matter, nitrogen (N), and phosphorus (P) from wastewater. The ownership of these facilities is both public and private. However, the environmental performance of the wastewater

treatment process is monitored by the public water regulator. This regulatory body ensures that the effluent discharged from the WWTPs complies with the European Union's legal requirements, specifically the European Urban Wastewater Directive (91/271/ECC).

The selection of response variables, predictors, and operating characteristics to assess eco-efficiency is based on data availability which was provided by the Catalan Water Agency for the year 2021. Given that one of the objectives of our study is to assess eco-efficiency, we define two response variables. The first is the operating costs of the wastewater treatment process, measured in euros per year. The second response variable is GHG emissions, measured in kilograms of CO_{2eq} per year. Statistical data about direct GHG emissions was not available for the analyzed WWTPs and therefore, according to past research (Gémar et al., 2018; Fallahiarezoudar et al., 2022), only indirect GHG emissions associated with the electricity consumption at WWTPs were considered. This is a limitation of the study which might be overcome in future studies if WWTPs monitor and collect data about direct GHG emissions. The average GHG emission factor of Catalonia for 2021 was employed, i. e., 259 gCO_{2eq}/kWh (Catalan Office for Climate Change, 2021). These variables are commonly used in the literature (Ananda and Hampf, 2015; Ananda, 2018). We also define four predictor variables based on the types of pollutants removed from wastewater and the volume of wastewater treated (Eq. 8).

$$PV_{ij} = WV_j * \left(Pollutant_{iij} - Pollutant_{eij} \right) \tag{8}$$

where PV_{ij} is the annual quantity of pollutants removed from wastewater for each pollutant i and WWTP j measured in kg/year; WV_j is the volume of wastewater treated by the WWTP j measured in m^3/year; $Pollutant_{iij}$ denotes the concentration of each pollutant i in the influent (i) of the plant j measured in kg/m^3 and $Pollutant_{eij}$ is the concentration of each pollutant i in the effluent (e) of the plant j measured in kg/m^3. Hence, the four predictor variables are the volume of wastewater treated adjusted by organic matter (expressed as chemical oxygen demand, COD), SS, N and P removal expressed in kg/year.

For each WWTP, the Catalan Water Agency provided data for the 6 variables considered in this study. Therefore, the database used to evaluate the eco-efficiency of 109 WWTPs embraces 654 data. Table 1 reports the descriptive statistics of the variables used in the case study.

3. Results and discussion

3.1. Optimal operational costs and GHG emissions

One of the advantages of EAT approach is its capability to identify which predictive variables (pollutants removed) statistically influence in the response variables (operational costs and GHG emissions). Based on the 654 data compromising our database, only the amount of COD and SS removed from wastewater have a statistically significant influence on the operational costs and GHG emissions of the assessed WWTPs (Fig. 1). This is because these two pollutants are the ones that are removed in greater quantities from wastewater (Table 1). For those WWTPs removing more than 12,068,782 kg of COD per year, the estimated maximum operating costs and GHG emissions should be 9,915,457 €/year and 10,039,318 kg CO_{2eq}/year, respectively. In contrast, if the quantity of COD removed in WWTPs is less than

12,068,782 kg, the maximum operational costs and GHG emissions should be 3,269,392 €/year and 1,872,141 kg CO_{2eq}/year, respectively. Hence, maximum operating costs for the assessed WWTPs are between 0.27 €/kg COD and 0.82 €/kg COD whereas maximum GHG emissions are between 0.16 kg CO_{2eq}/kg COD and 0.83 kg CO_{2eq}/kg COD.

Regarding the removal of SS, the maximum operating costs and GHG emissions for those WWTPs removing less than 2,262,235 kg SS/year are 2,272,776 €/year and 778,981 kg CO_2eq/year. On the contrary, if the WWTP removes more than 2,262,235 kg SS per year, the maximum operating costs increase up to 3,269,392 €/year and GHG emissions up to 1,872,141 kg CO2eq/year. Hence, optimal operating costs for the assessed WWTPs are between 1.00 €/kg SS and 1.45 €/kg SS whereas optimal GHG emissions are between 0.34 kg CO_{2eq}/kg SS and 0.83 kg CO_{2eq}/kg SS.

From a policy perspective, the Catalan Water Agency applies a fee of 1.0023€/kg COD and 0.5011 €/kg SS for discharging industrial wastewater to the municipal sewer system (ACA, 2020). However, this fee does not consider the size of the WWTP which notably influences on their operational costs due to the presence of economies of scale (Hernández-Chover et al., 2018; Caldas et al., 2019). The estimated optimal values of operating costs could be used to set more specific wastewater discharge fee values according to WWTPs´ size. Moreover, given the relevance of reducing the carbon footprint of WWTPs, the estimated optimal GHG emissions are useful for defining progressive targets for reducing GHG emissions in wastewater treatment processes.

3.2. Eco-efficiency of WWTPs

Eco-efficiency scores of the 109 assessed WWTPs are between 0.051 and 1.000 (Fig. 2) with an average value of 0.373 (see supplemental material for eco-efficiency scores for each facility). It involves that operating costs and GHG emissions of WWTPs could go down by 62.7% to remove the same quantity of pollutants. It reveals that the economic and environmental performance of the evaluated WWTPs is poor. Average eco-efficiency scores estimated by previous studies presented a wide range between 0.240 and 0.929. In the case of Spanish WWTPs, Molinos-Senante et al. (2014), Gómez et al. (2018) and Mocholi-Arce et al. (2020) reported similar average eco-efficiency scores, i.e., 0.598, 0.454 and 0.480, respectively. On contrary, Ramírez-Melgarejo et al. (2021) reported an average eco-efficiency score of 0.929 also for Spanish WWTPs. It should be noted that only seven WWTPs embraced the sample of this study, and 5 variables were integrated in the eco-efficiency model. Hence, DEA estimations present limited discriminatory power due to the lack of freedom degrees. In the case of Chinese WWTPs, diverges in average estimated eco-efficiency are also evident. On the one hand, Dong et al. (2017) for a sample of 736 WWTPs reported a mean eco-efficiency of 0.62. On the other hand, average eco-efficiency estimated by Xi et al. (2023) for 1044 WWTPs was 0.240. Hence, eco-efficiency results using the EAT method are consistent with those from previous studies based on DEA methodology.

In order to get a better understanding of how eco-efficiency scores are distributed across WWTPs, Fig. 3 shows eco-efficiency distributions. It is shown that 47 out of 109 WWTPs (43%) present an eco-efficiency lower than 0.20. This means that this group of facilities need to reduce operational costs and GHG emissions up to 80% to catch-up with

Table 1
Descriptive statistics to estimate eco-efficiency scores.

Variables	Unit of measurement	Average	Std. Dev.	Minimum	Maximum
Operational costs	Euros/year	758,298	1,409,069	18,976	9,915,457
Greenhouse gas emissions	kgCO2eq/year	411,307	1,275,428	2338	10,039,318
COD removed	kg/year	2,791,539	11,680,492	2567	106,021,387
SS removed	kg/year	1,504,366	6,932,355	893	67,171,650
N removed	kg/year	149,680	536,491	163	4,152,857
P removed	kg/year	35,558	164,284	16	1,506,131
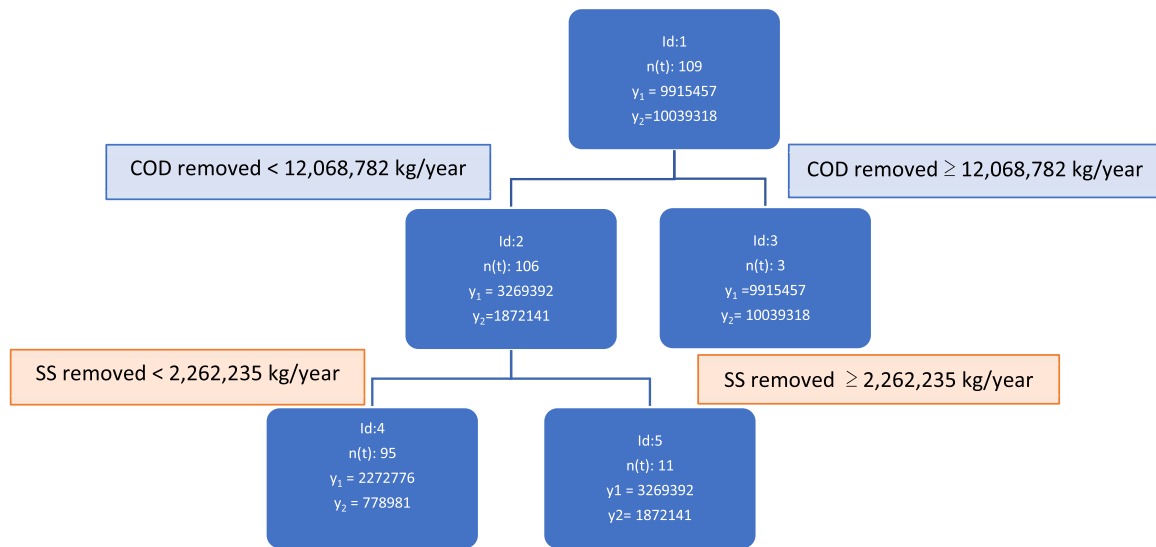
Fig. 1. Efficiency Analysis Tree (EAT) for estimating operating costs and greenhouse gas emissions, *where: Id denotes the node; n(t) shows the number of observations, y_1 is the maximum operating costs in €/year and y_2 is the maximum level of greenhouse gas emissions in kg $CO2_{eq}$/year.*
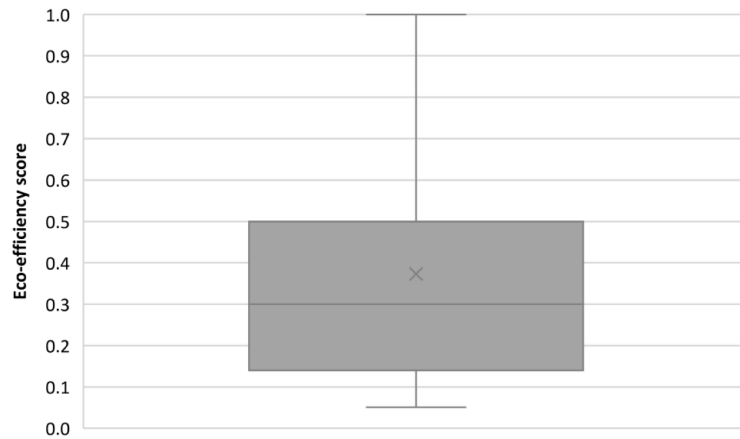
Fig. 2. Statistics of the eco-efficiency estimations for assessed WWTPs.
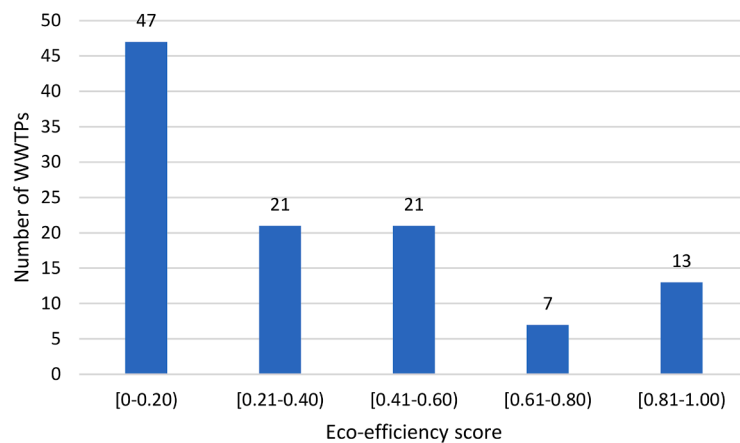
Fig. 3. Distribution of eco-efficiency scores across WWTPs.

the most efficient ones. There are 42 WWTPs (39%) who report an average eco-efficiency ranging from 0.21 to 0.60. The potential savings in operating expenditure and GHG could range between 40% and 80% on average for these facilities. In contrast, there are a reduced number of WWTPs who performed relatively better than others. In particular, it is found that 7 WWTPs (6%) reported an eco-efficiency score between 0.61 and 0.80. Although the performance of this group could be considered satisfactory, there is considerable room for improving economic and

environmental efficiency. Finally, there are 13 WWTPs (12%) who belong to the most eco-efficient group as their scores range between 0.81 and 1.00. Nevertheless, there are only four WWTPs whose eco-efficiency score is one which means they are eco-efficient (Table 2).

3.3. Estimation of operational cost savings and GHG emission reductions

Eco-inefficient WWTPs, i.e., those whose eco-efficiency score is less than one, present room to reduce operational costs and GHG emissions by removing the same quantity of pollutants from wastewater. According to Eq. (6), operational cost savings were estimated for the 109 assessed WWTPs (Fig. 4). Based on the eco-efficiency scores for the 109 WWTPs and their current operational costs, potential cost savings are estimated to be 46,959,370 €/year. The mean potential operational cost savings for the assessed WWTPs is 0.32 €/m^3 whereas the 25th and 75th percentiles are 0.95 €/m^3 and 0.486 €/m^3, respectively.

Reducing operational costs of WWTPs could have positive effects for people if savings are passed to customers in terms of lower wastewater treatment tariffs. Currently, the average water and wastewater tariff in Catalonia (where the assessed WWTPs are located) is 2.44 €/m^3 (ACA, 2023). It includes both drinking water and wastewater collection and treatment services for a water consumption of 12 m^3/month[1]. Hence, average potential cost savings in WWTPs (0.32 €/m^3) might involve a 13.1% reduction on the average water and wastewater tariff for customers.

Focusing on GHG emissions, eco-inefficient WWTPs could save 27,632,201 kgCO$_{2eq}$/year if they were eco-efficient. Notable differences are observed among assessed WWTPs (Fig. 5). The average potential reduction of GHG emissions for the WWTPs is 0.107 kgCO$_{2eq}$ /m^3 whereas the 25th and 75th percentiles are 0.043 kgCO$_{2eq}$ /m^3 and 0.130 kgCO$_{2eq}$ /m^3, respectively. Reducing GHG emissions from WWTPs could contribute to achieve 2030 GHG reduction targets defined for Catalonia and Spain which are −22% and −27% vs. 1990, respectively (OCCC, 2023).

3.4. Detailed analysis of best and worst WWTPs

Wastewater treatment plant-specific results on eco-efficiency, potential savings in costs and GHG along with some information on their technology and treatment used are reported in Table 2. The analysis refers to the 10 most and 10 less eco-efficient WWTPs. The results show that the most eco-efficient group consists of facilities with scores ranging from 0.891 to 1.000. The majority of the most eco-efficient plants are large facilities that remove high volumes of organic matter and SS. There are four WWTPs that are found to be fully eco-efficient, i.e. their efficiency score is 1.000. Two of these four facilities treat small volumes of wastewater using a concentric chambers reactor. The other two fully eco-efficient plants are large ones that use conventional activated sludge to treat wastewater. This result evidences that while WWTPs present economies of scale (Hernández-Chover et al., 2018), small-scale facilities can be eco-efficient. The rest of the top eco-efficient plants reported eco-efficiency scores that ranged from 0.892 to 0.952. This means that on average these plants could cut down operating costs and GHG emissions from 4.8% to 10.9%. From a technological perspective, the top eco-efficient present heterogenous secondary treatment, i.e., carrousel, biofilter, conventional activated sludge and concentric chamber. The presence of heterogeneity in the technology used to treat sewage sludge is indeed apparent. Within the top 10 WWTPs in terms of eco-efficiency, various treatment methods such as aerobic digestion, anaerobic digestion, and composting are employed for sludge treatment. Interestingly, these same treatment methods are also utilized by the

worst 10 WWTPs in terms of eco-efficiency. This observation suggests that the choice of sludge treatment technology alone does not guarantee high eco-efficiency. Other factors such as operational practices, maintenance, resource allocation, and overall management of the treatment process can significantly influence the eco-efficiency outcomes.

In terms of the WWTPs that performed poorly in terms of economic and environmental efficiency, it is shown that these plants are mainly of moderate or large size. The poor performers remove high volumes of pollutants using conventional activated or carrousel secondary treatment technology. None of the ten worst WWTPs use either concentric chamber reactor or biofilter as secondary treatment. Their eco-efficiency scores do not exceed 0.10 which means that operating costs and GHG emissions should cut down by 90% on average to deliver the same level of wastewater services. Therefore, the potential savings in costs and GHG are substantial. This means that the worst performers need to make substantial improvements to catch-up with the most efficient ones in the sector.

4. Conclusions

Conducting a thorough evaluation of the eco-efficiency of wastewater treatment plants (WWTPs) is crucial for enhancing their sustainability and facilitating the transition to a circular economy. Previous research has predominantly employed the deterministic Data Envelopment Analysis (DEA) method to assess the eco-efficiency of WWTPs. However, DEA is susceptible to overfitting issues. In contrast, our study utilizes the Efficiency Analysis Tree (EAT) method to estimate eco-efficiency scores for a sample of WWTPs. The EAT approach provides a more robust and reliable assessment, overcoming the limitations of DEA. Additionally, the EAT method enables the quantification of optimal operational costs and greenhouse gas (GHG) emissions based on the removal of chemical oxygen demand (COD) and suspended solids (SS) in the WWTPs. This comprehensive analysis offers valuable insights into improving the economic and environmental performance of WWTPs.

The main findings of this study can be summarized as follows. Optimal costs and GHG emissions from operating WWTPs depend on the quantity of COD and SS removed from wastewater. Hence, different targets in terms of reducing operational costs and GHG emissions should be defined by the regulator to WWTPs. Secondly, only 4 out of 109 WWTPs (3.7%) are eco-efficient. It involves that 105 facilities present room to save costs and reduce GHG emissions. In particular, WWTPs could save on average 0.32 €/m^3 and 0.11 kgCO$_{2eq}$/m^3 if they were eco-efficient. The results showed that the average eco-efficiency was 0.373 meaning that operating expenditure and GHG emissions should cut down by 62.7% to deliver the same level of wastewater services. Equivalently, the potential savings in operating costs and GHG could reach the level of 46,959,370 euros per year and 27,632,201 kg of CO2$_{eq}$ per year. The analysis of the best and worst WWTPs in terms of eco-efficiency illustrated that the size and secondary treatment of the facilities does not exclude them to be eco-efficient.

The results of our analysis hold significant policy implications for several reasons. Firstly, by employing a novel method that combines machine learning and linear programming techniques, we provide policymakers with valuable insights into the environmental and economic efficiency of wastewater treatment processes. This method enables policymakers to determine the maximum levels of operating expenditure and carbon emissions that can be achieved by treating different levels of pollutants. As a result, policy decisions can be more targeted and effective. Secondly, our approach overcomes the overfitting issues commonly associated with other non-parametric techniques, ensuring that the efficiency scores obtained are reliable. This enhances the credibility and usefulness of the results for policy formulation. Furthermore, policymakers gain a comprehensive understanding of the efficiency of the wastewater treatment process in terms of both economic and environmental performance. This knowledge facilitates the

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[1] Volumetric water and wastewater tariffs in Catalonia are based on increasing blocks scheme and therefore, volumetric cost (€/m^3) depend on the volume of water consumed.

Table 2
Characteristics of the top and bottom eco-efficient WWTPs.

Ranking of WWTPs	Eco-efficiency	GHG savings (kgCO2$_{eq}$/year)	Operating costs savings (€/year)	COD removed (kg/year)	SS removed (kg/year)	N removed (kg/year)	P removed (kg/year)	Secondary treatment type *	Technology for treating sewage sludge**
1	1.000	-	-	3921	1618	163	38	CC	AD
1	1.000	-	-	5,011,285	2,262,235	431,869	57,475	AS	AnD
1	1.000	-	-	2567	893	224	16	CC	AD
1	1.000	-	-	12,068,782	7,192,405	659,981	104,051	AS	AD
5	0.952	44,391	87,651	4,141,107	2,375,993	355,528	95,502	BF	AnD
6	0.938	65,419	121,426	3,780,230	2,412,097	277,183	47,145	AS	AnD
7	0.932	53,130	185,161	4,361,462	2,426,963	3156	18,326	BF	AD
8	0.900	7189	21,211	293,222	189,028	26,294	4260	AS	C
9	0.900	7005	38,246	292,403	178,636	27,187	3733	CC	AD
10	0.891	108,717	29,102	5,293,607	2,540,008	286,029	82,673	CS	AD
100	0.100	701,084	1,637,666	4,959,690	2,072,431	189,613	37,209	AS	AD
101	0.100	442,164	757,925	4,452,943	2,127,641	125,688	50,245	AS	C
102	0.100	74,351	467,096	252,084	101,590	26,625	2463	CS	C
103	0.100	157,137	384,665	1,809,265	695,901	164,770	22,610	AS	AnD
104	0.100	430,766	1,272,295	3,924,433	2,256,309	240,258	35,601	AS	AnD
105	0.100	133,110	323,272	267,684	128,447	41,511	4846	CS	AD
106	0.100	549,512	111,516	2,814,881	1,144,778	221,217	32,510	AS	AD
107	0.100	530,096	65,390	3,769,839	1,300,499	232,748	36,335	AS	C
108	0.090	104,799	36,268	295,429	153,783	21,892	3314	CC	AD
109	0.051	31,466	2,010,446	50,712	28,510	7420	1135	CS	AD

* CC denotes concentric chamber; AS denotes conventional activated sludge; BF denotes biofilter; and; CS denotes carrousel.

** AD denotes aerobic digestion; AnD denotes anaerobic digestion; and C denotes composting.
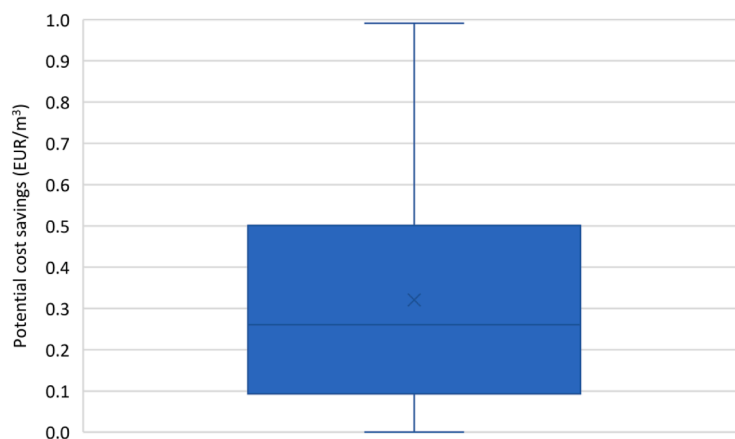
Fig. 4. Statistics of potential operational cost savings for assessed WWTPs.
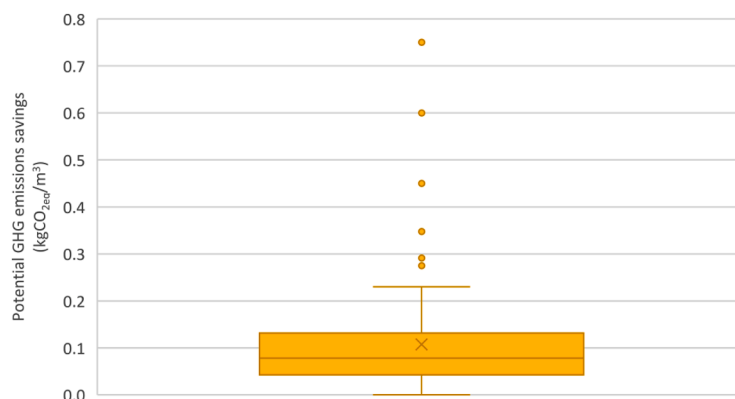
Fig. 5. Statistics of potential GHG emissions reduction for assessed WWTPs.

quantification of potential savings in operating expenditure and carbon emissions. Additionally, it enables policymakers to identify the best and worst performers among the WWTPs, highlighting the degree of catch-up required to reach the frontier of eco-performance. Lastly, the findings of our analysis can inform business decision-making processes by suggesting potential best practices that can be adopted to enhance eco-performance. This information is valuable for WWTP managers and operators, enabling them to implement strategies for improving their

operational and environmental efficiency. Overall, our study's results provide policymakers with actionable insights that can guide policy decisions, facilitate resource allocation, and promote the adoption of best practices to drive improvements in eco-performance within the wastewater treatment sector.

While this study introduced a novel methodological approach to benchmark the eco-efficiency of WWTPs, it is important to acknowledge its limitations. Two notable limitations are as follows. Firstly, the study focuses on indirect GHG emissions, overlooking the direct emissions associated with wastewater treatment. Future research in this area could address this gap by incorporating the monitor and assessment of direct GHG emissions in WWTPs. Integrating both indirect and direct emissions would provide a more comprehensive understanding of the overall environmental impact and enable a more accurate assessment of eco-efficiency. Secondly, the data utilized in this study only covers the year 2021. As WWTPs might implement various measures to improve their eco-efficiency over time, it would be useful to compare eco-efficiency across multiple years. This longitudinal analysis would help identify the policies and measures that contribute the most to enhancing eco-efficiency in WWTPs. It could highlight the effectiveness of specific initiatives and provide insights for the development of targeted strategies to continuously improve eco-efficiency in the future.

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.

Acknowledgment

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2023.120354.

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