



Assessing carbon and pollutant efficiency in wastewater treatment plants: A data-driven benchmarking framework using latent class stochastic frontier analysis

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ABSTRACT

Achieving carbon neutrality in wastewater treatment plants (WWTPs) presents a significant challenge, as reducing greenhouse gas (GHG) emissions must not compromise pollutant removal efficiency. This study introduces a novel Carbon and Pollutant Efficiency Index (CPEI) to benchmark the environmental performance of WWTPs by integrating GHG emissions and pollutant removal efficiency into a single metric. To address limitations in previous studies, which primarily relied on Data Envelopment Analysis (DEA), this research employs Latent Class Stochastic Frontier Analysis within a metafrontier framework to account for unobservable heterogeneities among WWTPs. A case study of 109 WWTPs in Spain identified three distinct operational classes, with average CPEI scores of 0.595, 0.586, and 0.506 for Classes 1, 2, and 3, respectively. Results indicate that chemical oxygen demand (COD) removal is the primary driver of GHG emissions, reflecting the energy-intensive nature of aerobic treatment processes. None of the WWTPs achieved full efficiency (CPEI = 1), suggesting substantial room for improvement. Policy implications include the need for tailored regulatory strategies that balance carbon reduction with pollutant removal targets. The proposed CPEI provides a robust decision-support tool for benchmarking WWTPs and guiding policies towards sustainable and decarbonized wastewater management.

1. Introduction

Access to sanitation is crucial for human well-being, environmental sustainability, and economic development (Hu et al., 2019). In high-income countries, the primary challenge is not ensuring access to sanitation, as coverage is nearly universal and approximately 70 % of generated wastewater is treated (UN, 2017). Instead, the focus lies on addressing emerging challenges in urban wastewater treatment such as climate change, demographic shifts, and newly emerging pollutants (European Environment Agency, 2019). Regarding climate change, the European Union Directive 2024/3019 concerning urban wastewater treatment mandates that wastewater treatment plants (WWTPs) progressively reduce their greenhouse gas (GHG) emissions in alignment with the EU's 2050 Climate Neutrality objective. However, this reduction must not compromise the efficiency of pollutant removal, ensuring

that environmental protection remains a priority.

To support decision-making in the context of multiple objectives and challenges, multi-criteria decision-making (MCDM) methods have been widely applied in wastewater treatment for various purposes. These include selecting appropriate technologies for WWTP improvements in specific scenarios (Eseoglu et al., 2022), assessing the sustainability of wastewater treatment technologies (Gherghel et al., 2020; Ling et al., 2021; Attri et al., 2022), and benchmarking WWTP performance by integrating multiple key performance indicators (KPIs) into a single synthetic index (Henriques et al., 2022; Pereira et al., 2023; Wu et al., 2019). Within this category, given the growing emphasis on reducing GHG emissions in wastewater treatment, several studies have incorporated GHG emissions as a key KPI alongside others for WWTP performance assessment (Chen et al., 2023; Gómez et al., 2018; Ramírez-Melgarejo et al., 2021; Sala-Garrido et al., 2023; Xi et al.,

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2023). These studies revealed the importance of incorporating carbon emissions alongside pollutant removal efficiency into a single index to holistically benchmark WWTP performance. Such an approach provides a comprehensive assessment that facilitates the identification of current performance levels and improvement opportunities at the WWTP level.

Despite significant contributions to the literature and knowledge on the carbon performance of WWTPs, previous studies (Chen et al., 2023; Gómez et al., 2018; Ramírez-Melgarejo et al., 2021; Sala-Garrido et al., 2023; Xi et al., 2023) present two main limitations that need to be addressed. Firstly, all these studies employ Data Envelopment Analysis (DEA) as the MCDM method. DEA is a non-parametric technique that uses linear programming to construct a piecewise convex efficiency frontier (Ozcan, 2014) based on multiple inputs and outputs. Its primary advantage is that it does not require the specification of a functional form for the production frontier (Yang and Chen, 2021). However, DEA is highly sensitive to outliers, noise, and data errors, and as a deterministic approach, it does not distinguish between inefficiency and statistical noise, potentially leading to misclassification of efficiency. Additionally, Basic DEA models assume either constant returns to scale or variable returns to scale. However, these assumptions may not always reflect real-world production technologies (Ferreira et al., 2023). Secondly, previous studies that integrate GHG emissions into WWTP performance assessment assume that all facilities operate under the same production frontier (Gómez et al., 2018; Ramírez-Melgarejo et al., 2021; Xi et al., 2023). However, this assumption may not hold in practice due to variability in influent quality, wastewater treatment technologies, ownership structures, and other latent or unobservable differences among WWTPs. While a common production frontier can provide meaningful efficiency benchmarks under uniform technological conditions, it may oversimplify performance evaluations in contexts like wastewater treatment, where unobserved operational heterogeneity can significantly influence environmental performance (Alvarez et al., 2012).

To address the limitations of previous studies—namely, their reliance on DEA methods and the assumption of homogenous production frontiers—this study introduces two key innovations. First, we propose a novel Carbon and Pollutant Efficiency Index (CPEI) that integrates GHG emissions and pollutant removal efficiency into a single, synthetic benchmark metric. Second, the CPEI was estimated using a novel methodology which integrates latent class stochastic frontier analysis (LCSFA) within a metafrontier framework allowing to account for unobservable heterogeneities in assessed WWTPs. The specific research objectives are: i) to construct and estimate the CPEI for benchmarking WWTP environmental performance; and ii) to classify WWTPs into latent operational categories based on their efficiency patterns to inform more targeted policy interventions.

Within the framework of the transition to carbon-neutral WWTPs, this study makes several key contributions to the literature. It proposes and applies a novel synthetic index, CPEI, which integrates carbon emissions and pollutant removal efficiency into a single metric, providing a holistic approach to benchmarking WWTP performance. While existing studies rely exclusively on DEA, this research addresses its key limitations, including sensitivity to outliers, the assumption of a common production frontier, and the inability to distinguish inefficiency from statistical noise. Unlike previous studies that assume all WWTPs operate under a common production frontier, this study explicitly accounts for unobservable heterogeneities, enabling a more nuanced and context-specific efficiency analysis and improving the reliability of benchmarking results. From a policy perspective, this research provides a decision-support framework for designing tailored policies that promote decarbonization without compromising environmental protection.

2. Methodology

This section outlines the methodological approach used to develop

the proposed CPEI and also to assess and classify WWTPs based on this synthetic index. The proposed methodological approach integrates two key concepts such as metafrontier and LCSFA. The metafrontier framework provides a unified reference (the metafrontier) to compare the performance of decision-making units (WWTPs in this study) that operate under different conditions or belong to distinct groups (Dakpo et al., 2024). The metafrontier envelopes all group-specific frontiers and represents the global best practice technology available across all groups. It serves as a common benchmark for assessing the relative performance of all WWTPs, regardless of their group membership (Afsharian, 2017). On the other hand, LCSFA (Ananda and Oh, 2023) is used to analyze efficiency and heterogeneity within a dataset, particularly in cases where the population under study consists of distinct, unobservable (latent) subgroups (Renner et al., 2021).¹ LCSFA identifies unobservable (latent) subgroups of WWTPs based on their data (input and outputs). As such, the classification reflects underlying operational patterns that may not be directly captured by observable attributes.

In this case study, three main stages were subsequently applied as it is shown in Fig. 1.

Stochastic frontier analysis (SFA) is a parametric technique that models the functional relationship between GHG emissions and outputs generation (Eq. (1)). This approach, unlike non-parametric techniques, integrates two error components: noise (ν_i) and inefficiency (u_i):

$$\ln GHG_i = f(y_i; \alpha'_i) + \nu_i + u_i \quad (1)$$

where $\ln$ denotes logarithm, f denotes function, i is the WWTP under assessment, y is the set of outputs, and α is the set of parameters that the model estimates. The noise terms, ν_i , accounts for measurement error and other stochastic influences. It follows the standard normal distribution. The inefficiency term, u_i , reflects the deviations from the efficient frontier follows the half normal distribution.

Eq. (1) assumes that all units (WWTPs) operate under a common frontier, implying the use of a uniform production technology. However, WWTPs are often heterogenous due to differences in operating characteristics, regulatory frameworks, and access to resources (Ananda and Oh, 2023). Ignoring such technological differences in production processes can result in less robust and potentially biased efficiency scores (Kumbhakar et al., 2012). In this context, latent class approach assumes that the population consists of unobservable (latent) subgroups, each with distinct characteristics. This technique identifies these subgroups by clustering WWTPs based on their data patterns, which influence both the functional form and the parameters of the SFA model (Llorca et al., 2017).

In LCSFA, both the functional form of the stochastic frontier and the inefficiency distribution can vary across classes, i.e., WWTPs with different characteristics. The estimation process involves maximizing the likelihood function simultaneously for the latent class probabilities and the parameters of the stochastic frontier for each class (Eq. (2)) (Lattufe et al., 2023; Stetter et al., 2023). The specific LCSFA functional form applied in this study is detailed as follows:

$$\ln GHG_{ij} = \alpha_{oj} + \sum_{m=1}^M \alpha_{mij} \ln y_{mi} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^N \alpha_{mnij} \ln y_{mi} \ln y_{ni} + \nu_{ij} + u_{ij} \quad (2)$$

where j represents the class, i is the WWTP, and m and n correspond to the different outputs that influence GHG emissions. As a parametric approach, the estimated parameters of Eq. (2), i.e., α_{mij} , α_{mnij} , are the weights of each variable (pollutant and carbon emissions) integrated the CPEI. It involves that weights are endogenously estimated and do not are allocated by the analyst or decision-maker, reducing the subjectivity

¹ To enhance the transparency and robustness of our analysis, we also estimated the CPEI using a traditional DEA model whose formulation and results are shown in Supplemental Material.

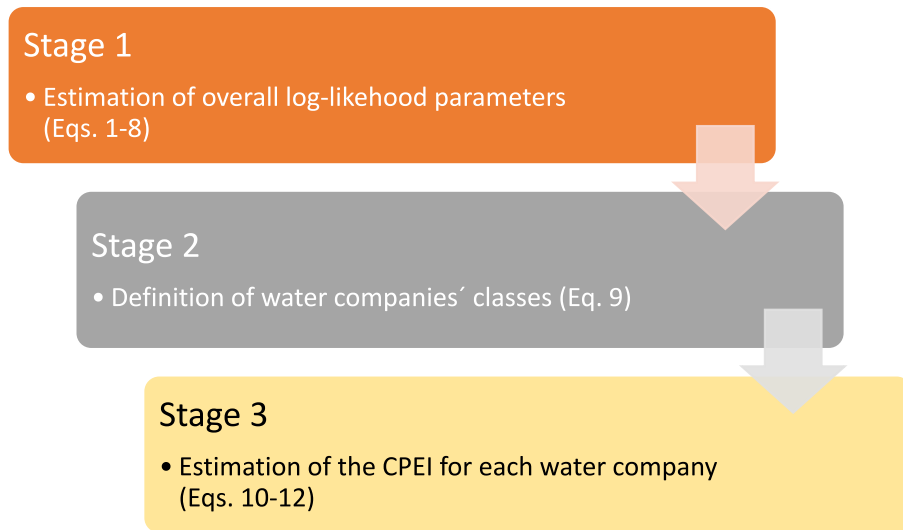


Fig. 1. Methodological stages of the study.

in the assessment.

Eq. (2) is estimated using maximum likelihood estimation techniques (Greene, 2005). The likelihood function of each WWTP i for each class j is defined as follows (Barros, 2011):

$$LF_{ij} = \frac{\Phi(\lambda_j \varepsilon_{ij} / \sigma_j)}{\Phi(0)} \frac{1}{\sigma_j} \phi\left(\frac{\varepsilon_{ij}}{\sigma_j}\right) \quad (3)$$

In Eq. (3), the likelihood function (LF) is defined as follows:

$$\varepsilon_{ij} = \ln GHG_{ij} - \alpha'_j y_i \quad (4)$$

$$\sigma_j = [\sigma_{uj}^2 + \sigma_{vj}^2]^{\frac{1}{2}} \quad (5)$$

$$\lambda_j = \frac{\sigma_{uj}}{\sigma_{vj}} \quad (6)$$

where ε_{ij} represents the residual term for WWTP i in class j , $\ln GHG_{ij}$ is the logarithm of GHG emissions, $\alpha'_j y_i$ is the estimated production frontier for class j , σ_j is the composite error term, and λ_j is the ratio of the inefficiency standard deviation (σ_{uj}) to the noise standard deviation (σ_{vj}). Additionally, ϕ represents the standard normal density function, and Φ denotes the cumulative distribution function (Barros, 2011).

The likelihood function for each WWTP was computed using Eq. (3), weighted by the prior probabilities of membership in class j , denoted as P_{ij} (Barros, 2009):

$$LF_i = \sum_{j=1}^J P_{ij} LF_{ij}, 0 \leq P_{ij} \leq 1, \sum_j P_{ij} = 1 \quad (7)$$

Thus, the overall likelihood function was calculated as follows (Lin and Du, 2014):

$$\log LF = \sum_{i=1}^K \log LF_i \quad (8)$$

The determination of the optimal number of classes (j) that capture technological heterogeneity was carried out using statistical measures such as the log-likelihood ratio test and Akaike Information Criterion (AIC) (Cullmann and Zloczyski, 2014; Frisvold and Atla, 2024). The optimal number of classes corresponds to the model with the lowest AIC values (Cullmann, 2012):

$$AIC = -2 \log LF(j) + 2\theta \quad (9)$$

where $\log LF(j)$ represents the value of the log-likelihood function for j class and θ denotes the number of estimated parameters.

After estimating the parameters of the overall log-likelihood in Eq. (8) enables the calculation of the CPEI for each WWTP, accounting for the specific production technology associated with each class j by solving Eqs. 10–12:

$$GHG_{ij} = E \left[\exp(-u_{ij}) \mid \varepsilon_{ij} \right] \quad (10)$$

The posterior probabilities for each class j , based on Bayes' theorem, were derived from the estimated parameters of the likelihood function (Greene, 2005; Alvarez and del Corral, 2010):

$$P(j|i) = \frac{P_{ij} LF_{ij}}{\sum_{j=1}^J P_{ij} LF_{ij}} \quad (11)$$

Using the posterior probabilities, the CPEI for each WWTP ($CPEI_i$) was calculated as:

$$CPEI_i = \sum_{j=1}^J (P_{ji} * GHG_{ij}) \quad (12a)$$

$CPEI_i$ ranges from 0 to 1. A value of 1 indicates that the WWTP operates at full efficiency, leaving no room for improvement. Conversely, a value below 1 suggests that there is potential for improvement, with the ultimate goal of achieving a score of 1.

3. Data sample and variables selection

The case study conducted in this research is based on a sample of 109 WWTPs located in the northeast of Spain. All facilities process urban wastewater through a series of treatments, including pretreatment, primary treatment, and biological secondary treatment, aimed at removing four main pollutants such as suspended solids (SS), organic matter, nitrogen (N), and phosphorus (P). All WWTPs ensure that their discharged wastewater complies with the legal thresholds established by the European Urban Wastewater Directive (91/271/ECC). The WWTPs are managed by a mix of public and private operators, with their environmental performance closely monitored by a public regulator.² Data for all variables used in this study were obtained from the public

² See more information in Supplemental Material. Dataset used in this study is available from the corresponding author upon reasonable request.

regulator and correspond to the year 2022.

The identification of outliers and atypical observations is a critical step in benchmarking the performance of WWTPs (Longo et al., 2023). A peer index approach (De Witte and Marques, 2010) was applied to the original dataset comprising 147 WWTPs to detect atypical observations. Consequently, 38 WWTPs were identified as outliers and removed from the dataset. This process resulted in a final sample of 109 WWTPs, for which the CPEI was estimated.

The selection of variables was guided by the primary objective of the study—assessing the carbon and pollutant removal efficiency of WWTPs—and by the availability of data, which is a significant constraint in large-sample assessments using real-world datasets (Amaral et al., 2022). Regarding GHG emissions, statistical data on direct emissions was not available for the analyzed WWTPs. Consequently, following previous research (Gemar et al., 2018; Sala-Garrido et al., 2011), this study considers only indirect GHG emissions associated with electricity consumption at the WWTPs, i.e., Scope 2 carbon emissions. At present, none of the 109 WWTPs assessed systematically monitor or report direct emissions (Scope 1), such as methane (CH₄) and nitrous oxide (N₂O) from biological processes and sludge treatment, nor indirect emissions from supply chains or infrastructure (Scope 3). As such, the lack of available data constrained the scope of this analysis. However, the recent adoption of the Urban Wastewater Treatment Directive (EU) 2024/3019 is expected to improve the availability of GHG emissions data in the near future. The Directive encourages member states to monitor and reduce methane emissions in line with the Global Methane Pledge, and to enhance transparency by making key information—such as treatment costs and environmental performance—publicly accessible, particularly for agglomerations above 10,000 population equivalents. This regulatory shift will likely support the inclusion of Scope 1 and Scope 3 emissions in future benchmarking studies. Consequently, the CPEI values presented in this study should be interpreted as partial indicators of carbon efficiency, reflecting operational energy-related emissions.

To estimate indirect emissions, the average GHG emission factor for Catalonia in 2022 was applied, which is 273 gCO_{2eq}/kWh (Catalan Office of Climate Change, 2022).

With regard to pollutants removed from wastewater, both the concentration of the main pollutants in the influent and effluent, as well as the volume of wastewater treated by each WWTP, were taken into account (Maziotis and Molinos-Senante, 2023). To achieve this, Eq. (12) was applied to each pollutant included in the assessment, namely SS, organic matter (measured as chemical oxygen demand, COD), N, and P:

$$PRV_{iz} = WWV_i * (Pollutant_{iz} - Pollutant_{eiz}) \quad (12b)$$

where PRV_{iz} presents the quantity of pollutant z removed annually from wastewater by WWTP i , expressed in grams per year (g/year); WWV_i denotes the volume of wastewater treated by the WWTP i measured in cubic meters per year (m³/year). $Pollutant_{iz}$ and $Pollutant_{eiz}$ refer to the concentrations of pollutants z in the influent and effluent of WWTP i , respectively, measured in grams per cubic meter (g/m³).

Table 1 reports the descriptive statistics of the variables used in this study.

4. Results and discussion

4.1. Parameters of the latent class stochastic frontier analysis (LCSFA) functional form

According to the methodological framework applied in this study, the LCSFA functional form (Eq. (2)) was estimated to define classes of WWTPs and calculate the CPEI for each WWTP. Based on the AIC parameters estimation, the optimal number of classes for the 109 assessed WWTPs was determined to be three. The AIC for one class was −474.2 ($\log LF = 241.5$), for two classes was −615 ($\log LF = 311.5$) and for three classes was −942.2 ($\log LF = 475.1$). Moreover, a LCSFA model with four classes did not converge, confirming that the optimal number of classes is three.

The results of the LCSFA functional form for each defined class are presented in Table 2. Regarding pollutants removed from wastewater, the estimated coefficients for the three classes and four pollutants are positive and statistically significant. This indicates that higher volumes of pollutants removed from wastewater are associated with higher levels of indirect GHG emissions. However, the impact of pollutant removal on GHG emissions varies among the classes. As shown in Table 2, the removal of chemical oxygen demand (COD) is the most influential pollutant on carbon emissions across the three defined classes of WWTPs. Specifically, a 1 % increase in the quantity of COD removed leads to an increase in indirect GHG emissions by 0.717 %, 0.497 %, and 0.572 % for classes 1, 2, and 3, respectively. This is because all 109 assessed WWTPs rely on aerobic processes to remove organic matter, which are considered energy-intensive processes (Molinos-Senante and Maziotis, 2023; Paraschiv et al., 2023).

Unlike the removal of COD, there is a notable discrepancy among the three identified classes regarding the pollutant that contributes the least to indirect carbon emissions. For WWTPs grouped in class 1, N removal is the least significant contributor, with a 1 % increase in N removal resulting in a 0.077 % increase in indirect GHG emissions. In class 2, P removal has the smallest impact, contributing 0.091 % for a 1 % increase in P removal. Finally, in class 3, SS removal contributes the least, with a 1 % increase in SS removal leading to a 0.049 % increase in indirect GHG emissions. From a policy perspective, these findings evidence the importance of adopting tailored energy-efficiency measures to the specific characteristics of each WWTP class and prioritizing interventions to balance pollutant removal efficiency with carbon emission reduction goals. The results presented in Table 2 highlight that latent heterogeneity among WWTPs can have a differential impact on environmental performance. For comparison purposes, the supplementary material includes the results of the standard SFA model (Eq. (1)), which assumes that all WWTPs operate under a common production technology. Although the standard SFA model similarly reveals that COD removal is the primary determinant of carbon emissions, it fails to capture the differences among classes regarding the contributions of other pollutants. These class-specific variations, which are critical for understanding the nuanced relationship between pollutant removal and GHG emissions, remain hidden under the assumption of homogeneous production technology.

Lambda (λ) refers to the ratio of the standard deviation of the inefficiency term (σ_u) to the standard deviation of the random noise term (σ_v). It is higher than zero and statistically significant in all three classes,

Table 1
Descriptive statistics of the wastewater treatment plants assessed.

Variable	Unit of measurement	Mean	Std. Dev.	Minimum	Max
Indirect greenhouse gas emissions	kgCO _{2eq} /year	411,307	1,275,428	2338	10,039,318
Organic matter removed (COD)	g/year	2,791,539	11,680,492	2567	10,6021,387
Suspended solids removed	g/year	1,504,366	6,932,355	893	67,171,650
Nitrogen removed	g/year	149,680	536,491	163	4,152,857
Phosphorus removed	g/year	35,558	164,284	16	1,506,131

Table 2

Estimates of the latent class stochastic frontier analysis production function.

Variables	Model parameters of latent class 1				Model parameters of latent class 2				Model parameters of latent class 3			
	Coeff.	Std. Err.	T-stat	St.Err.	Coeff.	Std. Err.	T-stat	St.Err.	Coeff.	Std. Err.	T-stat	St.Err.
Constant	0.138	0.014	9.608	0.000	0.093	0.054	1.700	0.089	0.084	0.126	0.666	0.506
P removed	0.113	0.017	6.551	0.000	0.091	0.018	4.969	0.000	0.218	0.073	2.987	0.003
N removed	0.077	0.014	5.373	0.000	0.233	0.043	5.405	0.000	0.128	0.032	3.984	0.000
SS removed	0.122	0.013	9.066	0.000	0.213	0.020	10.792	0.000	0.039	0.013	3.041	0.003
COD removed	0.717	0.026	27.317	0.000	0.497	0.029	17.295	0.000	0.572	0.116	4.933	0.000
σ	0.274	0.049	5.633	0.000	0.390	0.089	4.363	0.000	0.053	0.013	4.034	0.000
λ	0.599	0.110	5.450	0.000	0.483	0.068	7.147	0.000	0.286	0.053	5.353	0.000
Estimated prior probabilities for class membership					Coeff.		Std. Err.		T-stat		St.Err.	
Class1					0.540		0.084		6.435		0.000	
Class2					0.364		0.083		4.377		0.000	
Class3					0.096		0.030		3.205		0.001	
Log-likelihood					475.1							

indicating the presence of inefficiency among WWTPs and confirming that efficiency analysis is relevant and appropriate in this context.

4.2. Classes of wastewater treatment plants defined

According to the results presented in Table 2, the 109 assessed WWTPs were classified into three categories, whose main statistical characteristics, in terms of pollutant removal and GHG emissions, are detailed in Table 3. The distribution of WWTPs across these categories is notably uneven, with 73 facilities in Class 1, 22 in Class 2, and 11 in Class 3. On average, Class 1 WWTPs exhibit the highest performance in terms of pollutant removal and carbon emissions reduction. These facilities also process the largest volumes of wastewater. However, significant variability within this category highlights the need to enhance the performance of certain facilities. Conversely, Class 3 WWTPs, which treat intermediate volumes of wastewater, demonstrate moderate pollutant removal efficiency but exhibit the highest carbon emissions per cubic meter of treated water. This finding underscores the need for targeted interventions to improve their carbon footprint. Lastly, Class 2 WWTPs represent a middle ground, offering a balance between performance and consistency, though they still fall short of Class 1 in pollutant removal efficiency.

The coefficient of variation (CV) was computed as the ratio of the standard deviation to the average. Pollutant-related indicators show CV values greater than 100 %, reflecting substantial variability in pollutant load and removal performance among WWTPs within the same class. In contrast, GHG emissions per cubic meter treated exhibit CV values below 100 % across all classes, indicating more consistent emission patterns.

Table 3

Statistics of the classes of WWTPs.

Statistical parameter	Class of WWTP	GHG emitted (kg/m ³)	COD removed (g/m ³)	SS removed (g/m ³)	N removed (g/m ³)	P removed (g/m ³)	Volume treated (m ³ /year)
Average	Class 1	0.158	1418.385	583.348	102.259	15.299	4,626,609
	Class 2	0.180	989.925	546.070	75.355	11.127	3,188,083
	Class 3	0.168	357.487	188.319	32.796	4.521	2,471,536
Std. Dev	Class 1	0.099	5244.221	1897.472	349.771	53.535	16,724,011
	Class 2	0.153	2518.575	1318.610	186.192	28.243	5,301,253
	Class 3	0.068	232.316	126.304	16.211	2.936	3,278,035
Coefficient of variation (%)	Class 1	63	370	325	342	350	361
	Class 2	85	254	241	247	254	166
	Class 3	40	65	67	49	65	133
Minimum	Class 1	0.002	6.355	2.755	0.499	0.149	38,844
	Class 2	0.003	5.254	2.954	0.769	0.118	7844
	Class 3	0.098	36.396	13.659	5.285	0.145	73,540
Maximum	Class 1	0.600	38789.143	13381.272	2394.819	373.862	121,095,795
	Class 2	0.566	13000.168	6767.127	963.344	145.815	18,647,592
	Class 3	0.268	705.394	381.166	61.560	8.001	8,505,353

4.3. Carbon and pollutants efficiency index (CPEI)

Focusing on the CPEI estimated for each WWTP, Fig. 2 presents the statistics for each class. The average CPEI for WWTPs in classes 1, 2, and 3 was 0.595, 0.586, and 0.506, respectively. This indicates that WWTPs in Class 1 are the best performers in terms of pollutant removal efficiency and carbon emissions. However, it is important to note that none of the WWTPs in any of the three classes achieved a CPEI of 1, signifying that all 109 WWTPs have room for improvement in both carbon and pollutant removal efficiency. The maximum CPEI values for WWTPs in classes 1, 2, and 3 were 0.719, 0.718, and 0.559, respectively.

To provide insights into the practical potential for improvement, the CPEI gap between each WWTP's current performance and the maximum CPEI observed within its respective latent class was estimated. This benchmarking approach reflects realistic, achievable efficiency targets, rather than theoretical optima. For instance, in Class 1, the highest-performing WWTP reached a CPEI of 0.719, indicating that other facilities in this class could potentially improve their efficiency up to this level. Summary statistics on the potential efficiency gains across all classes are presented in Fig. 3.

To better understand the distribution of estimated CPEI across classes, Fig. 4 depicts the number of facilities falling within each CPEI range. Fig. 4 shows that none of the WWTPs have a CPEI lower than 0.2 or higher than 0.8, indicating that the 109 assessed facilities exhibit moderate levels of carbon and pollutant removal efficiency. Focusing on individual classes, 69 out of 73 WWTPs in Class 1 (94.5 %) have a CPEI ranging between 0.41 and 0.80. A similar pattern is observed for Class 2, where 24 out of 25 WWTPs (96.0 %) fall within the same CPEI range. In contrast, the 11 WWTPs in Class 3 show a more limited range of performance, with CPEI values exclusively between 0.41 and 0.60, and no

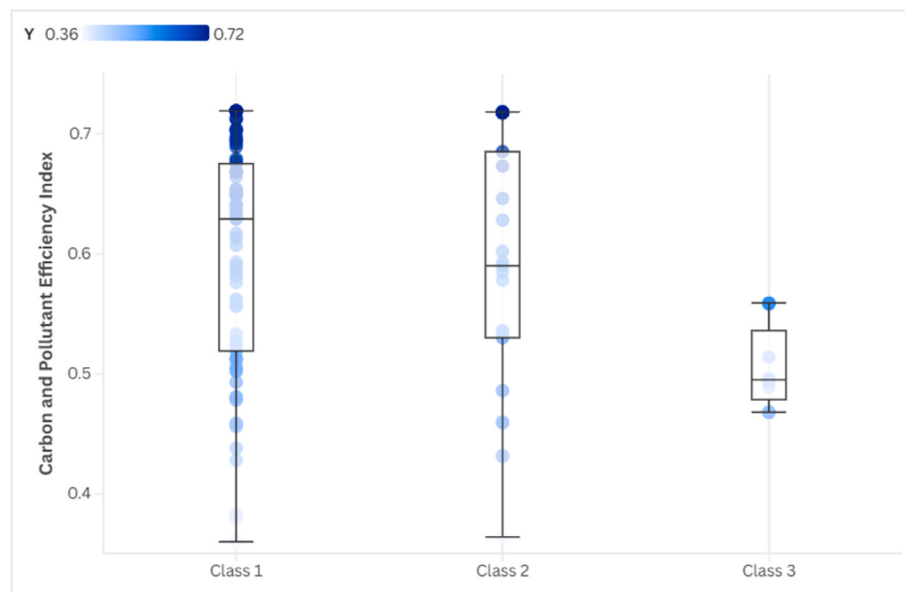


Fig. 2. Statistics of the carbon and pollution efficiency index for each class of wastewater treatment plants.

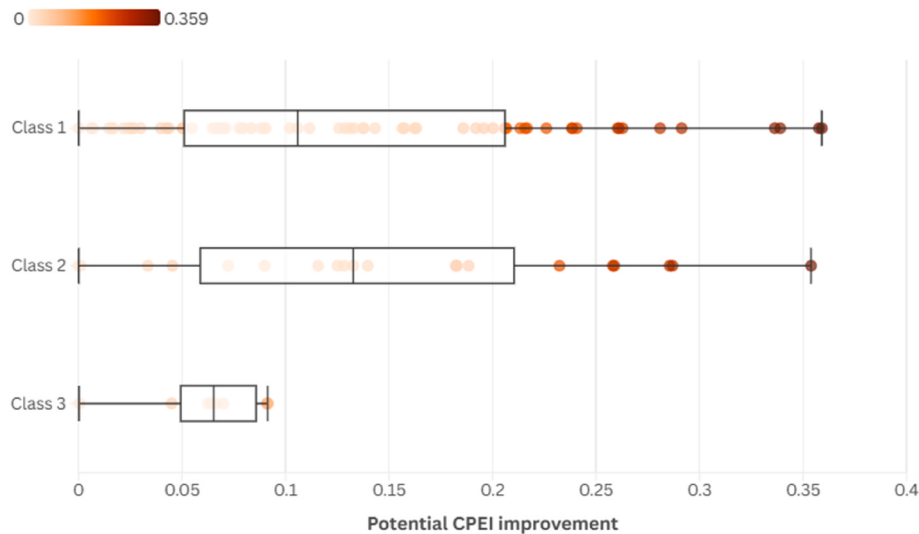


Fig. 3. Statistics of potential carbon and pollutant efficiency index improvement based on maximum score within each class.

facilities achieving higher performance levels.

These class-level differences in CPEI are consistent with the operational and performance profiles identified in Section 4.2. Class 1 WWTPs, which treat the highest volumes and remove the largest amounts of pollutants, also show the highest average CPEI (0.595), though still far from the efficiency frontier ($CPEI = 1$). This suggests that size and throughput alone do not guarantee high carbon-pollutant efficiency. Class 2 plants, with more balanced performance, show slightly lower average CPEI (0.586), while Class 3 facilities lag behind significantly ($CPEI = 0.506$), highlighting the operational challenges faced by medium-scale WWTPs with higher GHG emissions per unit of pollutant removed. These findings underscore the need for tailored regulatory and managerial strategies for each WWTP class.

Regarding technology or secondary treatment processes, it is important to note that these factors do not determine the classification of WWTPs into three classes. Instead, the LCSFA methodological approach groups WWTPs based on unobservable or latent differences related to their operational performance. Fig. 5 presents the average CPEI for each type of secondary treatment across the three WWTP

classes. Regardless of classification, facilities utilizing biofilters as secondary treatment exhibit the highest average CPEI, with values of 0.609, 0.664, and 0.558 for classes 1, 2, and 3, respectively. Conversely, WWTPs employing a complete mix scheme demonstrate the lowest average CPEI, with values of 0.588, 0.536, and 0.468 for classes 1, 2, and 3. Biofilters operate as an attached-growth process, where microorganisms adhere to a medium, whereas complete mix systems rely on suspended-growth microorganisms. In this context, previous studies (An et al., 2018; Molinos-Senante et al., 2015) have reported that secondary wastewater treatment technologies based on attached-growth processes offer superior sustainability. In terms of variability within each WWTP class, Class 1 exhibits minimal differences across secondary treatment types, suggesting that this variable has little influence on CPEI. In contrast, Class 2 displays the highest variability, with a difference of 0.129 between the maximum and minimum average values.

The results presented have significant policy and managerial implications for optimizing the performance of WWTPs. Notably, no WWTPs achieved CPEI values below 0.2 or above 0.8, indicating that current operational and technological configurations largely fall within a

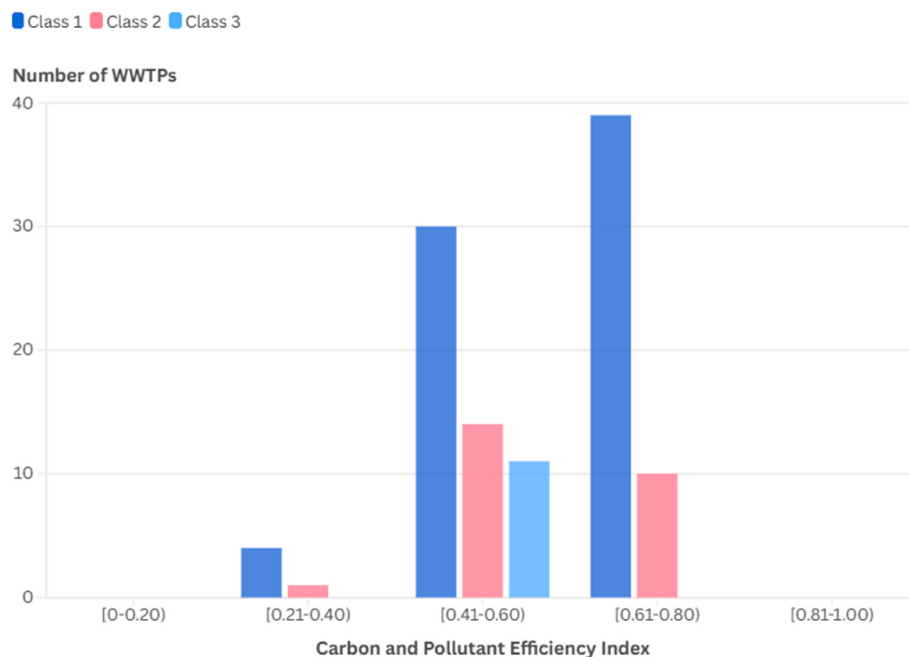


Fig. 4. Distribution of carbon and pollution efficiency index across classes of wastewater treatment plants.

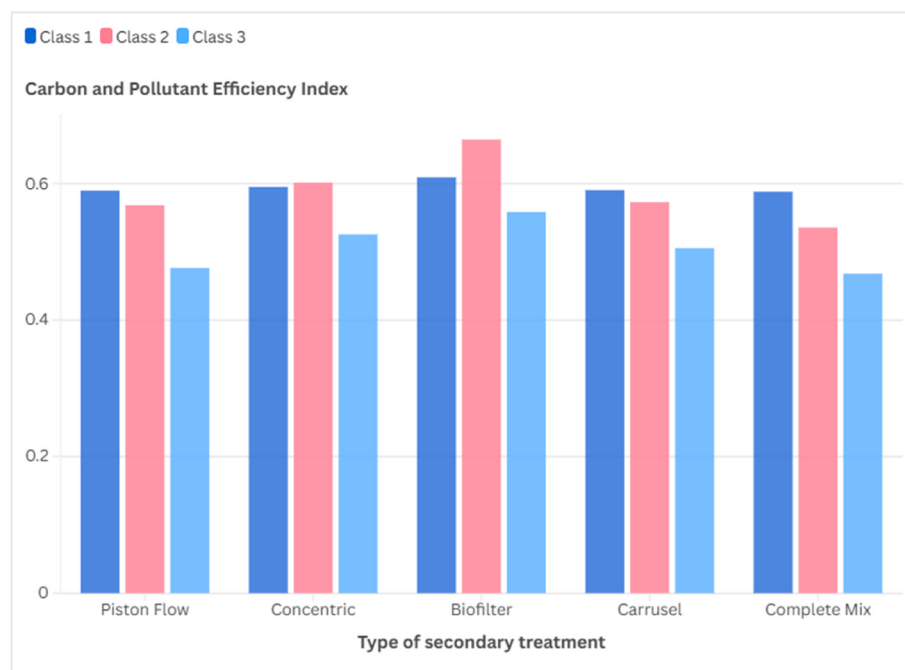


Fig. 5. Average carbon and performance index for each type of secondary treatment and class.

moderate efficiency range. Consequently, policymakers should prioritize strategies that foster incremental efficiency improvements, particularly within the 0.41–0.80 range observed in WWTPs classified under Classes 1 and 2. For WWTPs categorized under Class 3, where performance is worst, a more targeted approach is necessary. Specific funding mechanisms, technical assistance programs, and regulatory support should be developed to address operational bottlenecks, upgrade aging infrastructure, and enhance process control measures. Implementing best practices from high-performing WWTPs could also provide valuable insights for improving these facilities. Moreover, the absence of WWTPs attaining a CPEI above 0.8 highlights a critical gap in achieving high-efficiency, low-carbon wastewater treatment. This underscores the

need to establish ambitious yet realistic performance benchmarks that align with broader climate and water quality policies. Setting stringent but achievable carbon reduction and pollutant removal targets could serve as a catalyst for advancing technological innovation and encouraging the adoption of energy-efficient and resource-recovery-oriented treatment processes.

The CPEI can serve as a practical decision-support tool in several ways. For policymakers, the index enables the classification of WWTPs by performance tier, providing an empirical basis for differentiated regulatory strategies. For example, WWTPs in Class 3, with lower CPEI scores, could be prioritized for funding programs, technical assistance, or mandated performance audits. In contrast, WWTPs in Classes 1 and 2

might be encouraged to voluntarily adopt advanced energy-efficiency measures or pursue performance-based incentives.

For WWTP operators, the CPEI provides a concise, quantifiable measure of integrated environmental performance. This enables benchmarking across similar facilities, tracking improvements over time, and identifying specific operational practices associated with higher carbon-pollutant efficiency. The classification into latent performance groups can also guide investment decisions—for instance, by showing which technology upgrades are most impactful within each operational context. Moreover, as data availability expands (e.g., through the EU Directive, 2024/3019), the CPEI framework can be adapted to incorporate Scope 1 and Scope 3 emissions and increasing its value as a regulatory and management tool.

From a broader sustainability perspective, the observed moderate CPEI levels suggest that attaining carbon neutrality in wastewater management will require a paradigm shift in both technology and operational practices. This entails the integration of advanced treatment technologies, such as anaerobic digestion with biogas recovery, enhanced nutrient recycling, and the incorporation of renewable energy sources within WWTP operations (Kanchanamala Delanka-Pedige et al., 2021; Obaideen et al., 2022). To ensure coherence with broader sustainability goals, policymakers and wastewater managers should align WWTP improvement efforts with regional and national climate change mitigation strategies. Embedding wastewater treatment advancements within circular economy frameworks, carbon pricing mechanisms, and green infrastructure planning will be essential for enhancing long-term environmental and economic resilience (Möslinger et al., 2023; Ragazou et al., 2024; Soo and Shon, 2024).

5. Conclusions

Reducing carbon emissions from wastewater treatment is particularly challenging, as it must not compromise pollutant removal efficiency, ensuring that environmental protection remains a priority. Consequently, WWTPs must address multiple environmental objectives simultaneously. This study introduces and estimates a synthetic index—CPEI—which integrates GHG emissions and pollutant removal efficiency into a single metric. By employing an innovative methodological approach that combines LCSFA with a metafrontier framework, this study overcomes key limitations of previous studies that relied solely on DEA. The findings offer a more nuanced and context-sensitive efficiency assessment, recognizing latent heterogeneities among WWTPs and enhancing the reliability of benchmarking results.

The case study of 109 WWTPs revealed the presence of three distinct latent classes, each characterized by differences in operational efficiency and pollutant removal performance. The results indicate that COD removal is the primary driver of GHG emissions across all classes, underscoring the energy-intensive nature of aerobic biological treatment processes. The CPEI analysis revealed that no WWTP achieved full efficiency (CPEI = 1), and the highest observed scores in Classes 1 and 2 remain below 0.72. This consistent underperformance across all classes reflects systemic inefficiencies that may stem from outdated technology, insufficient process control, or scale mismatches. The average CPEI values — 0.595 (Class 1), 0.586 (Class 2), and 0.506 (Class 3) — align with the operational patterns identified in Section 4.2 and provide empirical support for differentiated policy responses. For instance, while large-scale WWTPs (Class 1) exhibit the best pollutant removal performance, their high energy use for COD treatment impacts on their carbon footprint, indicating a trade-off that regulators must address. In contrast, Class 3 WWTPs show uniformly low efficiency, calling for prioritized intervention. Thus, the CPEI not only quantifies performance but also provides relevant information to define targeted and evidence-based strategies for decarbonizing wastewater treatment operations.

From a policy and regulatory perspective, these findings offer valuable insights for developing targeted strategies to promote carbon neutrality in wastewater treatment. Since no WWTPs achieved high

efficiency (CPEI >0.8), policy measures should prioritize incremental efficiency improvements through energy optimization, process control enhancements, and infrastructure upgrades. Specific interventions—such as targeted funding mechanisms, technical assistance programs, and performance-based incentives—should be implemented to support underperforming WWTPs, particularly those in Class 3. Additionally, the study underscores the need for more ambitious carbon reduction and pollutant removal benchmarks in the wastewater sector. Establishing stringent yet realistic targets can drive technological innovation and encourage the adoption of energy-efficient and resource-recovery-oriented treatment processes. The proposed CPEI offers concrete value for improving the environmental regulation of WWTPs. It provides regulators with a robust tool for performance-based policy targeting and provides WWTP operators with a single, interpretable benchmark for tracking and improving integrated environmental performance. As wastewater utilities face increasing decarbonization pressure, such tools will be essential to meet climate and water quality goals simultaneously.

Although the use of LCSFA within a metafrontier framework offers a nuanced approach that captures latent operational differences among WWTPs, it also introduces methodological complexity. The estimation of latent class models relies on model selection criteria and assumptions that may affect reproducibility and interpretability. Moreover, the aggregation of multiple environmental indicators into a single index—while useful for synthesis—can obscure trade-offs among pollutants if not complemented by disaggregated analysis. The CPEI, as proposed, focuses on Scope 2 carbon emissions and does not include Scope 1 and Scope 3 emissions. Future work could refine the index to integrate broader emissions profiles and test alternative aggregation strategies.

CRedit authorship contribution statement

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2025.146413>.

Data availability

Data will be made available on request.

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