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Benchmarking energy efficiency in water utilities: Evidence from England and Wales

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ABSTRACT

Production and distribution of drinking water is an energy intensive process. Understanding the energy efficiency of drinking water services and what drives efficiency could improve sustainability of water cycle. In this study, we use the Efficiency Analysis Trees (EAT) method to benchmark the energy efficiency of several water utilities in England and Wales based on their energy consumption. Unlike traditional parametric and non-parametric methods previously used to assess the performance of water utilities, EAT does not suffer from overfitting. We further employ bootstrap truncated regression techniques to understand what drives energy performance. The results showed that the average energy efficiency of the English and Welsh water industry during the 2011–2020 period was 0.767. This means that energy consumption could be reduced by 23.3% while delivering the same level of water to customers. Equivalently, on average water utilities could potentially save 63,479 MWh per year. Water treatment complexity, source of raw water and population density were factors that influenced energy efficiency of drinking water supply processes. Conclusions of this study are useful to water regulators and water companies for informed decisions towards a low-carbon urban water cycle.

1. Introduction

Water is vital for humans and the environment. Ensuring that potable water is provided to all people at all times is part of United Nations' sustainability agenda (UN, 2015). Abstracting water from natural or artificial water bodies and treating it on drinking water treatment facilities to produce potable water requires high level of energy (Plappally and Leinhard, 2012; Majid et al., 2020; Khalkhali et al., 2021). Both the published literature and policy concur that a better understanding of the water-energy nexus is a priority (Chini et al., 2016).

Sustainable use of energy during the provision of water services could have economic and environmental benefits. An efficient use of energy could reduce energy costs which is the major determinant of operational costs of water utilities (Wilson et al., 2021). Evaluating the energy efficiency of the water processes and getting a good understanding of what drives energy performance of water companies could be a valuable tool for policy makers to provide drinking water services in a sustainable manner (Rodríguez-Merchan et al., 2021).

There were several studies in the past that investigated the water-energy nexus pointing out that society and policy makers need to ensure that energy should be used in a sustainable way when providing water services (e.g., Mercedes Garcia et al., 2021; Yang et al., 2022). However, as found in the literature reviews by Ahmad et al. (2020) and Zaman et al. (2021) most of past research on this topic focused on assessing the energy characteristics of water systems employing a set of performance indicators. Another group of studies focused on quantifying the energy used by water companies to provide drinking water (expressed in kWh/h) (Majid et al., 2021; Kiziltan, 2021; Alresheedi et al., 2022). Thus, the main limitation of past research is that energy efficiency of the water services was not evaluated. By contrast, energy efficiency assessment allows comparing the energy performance of a sample of water utilities through the development of a synthetic indicator embracing multiple variables (Molinos-Senante and Sala-Garrido, 2018).

While previous studies evaluated the energy efficiency of drinking water treatment plants (Sala-Garrido and Molinos-Senante, 2020;

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Molinos-Senante and Maziotis, 2022a) and wastewater treatment plants (Hernandez-Sancho et al., 2011; Molinos-Senante and Maziotis, 2022b), to best of our knowledge only the recent studies by Molinos-Senante et al. (2022a; 2022b) and Sala-Garrido et al. (2023) focused on assessing the energetic performance of water companies, i.e., including the stages of water abstraction, treatment and supply. Both studies estimated energy cost efficiency, i.e., they used energy costs as input variable rather than the volume of energy used by the water companies to evaluate their energetic performance. Because water companies might have different energy tariffs, energy costs might not be directly correlated with energy use. Moreover, past research (Molinos-Senante et al., 2022a; 2022b; Sala-Garrido et al., 2023) used the data envelopment analysis (DEA) method to estimate energy cost efficiency.

Despite the novelty of these previous studies, it should be noted that DEA just like Free Disposal Hull (FDH) are deterministic methods meaning that deviations from the efficiency frontier are due to inefficiency only. However, no functional form for the production technology is required and the efficient frontier is constructed using observed data. In the case of DEA, the efficient frontier takes the form of piecewise linear and convex, whereas the FDH frontier takes the form of a step function (Xiao et al., 2022). Both DEA and FDH suffer from overfitting (Esteve et al., 2020; 2021) making the efficiency scores less robust. Machine learning techniques such as Random Forests (Breiman, 2001), Gradient Boosting (Friedman, 2001), and Efficiency Analysis Trees (EAT) (Esteve et al., 2020) allow mitigating overfitting. Gradient Boosting and Random Forests primarily aim to minimize prediction error by aggregating results across multiple decision trees (El Baida et al., 2025; Matyukira and Mhangara, 2023). In contrast, EAT integrates machine learning with efficiency analysis by constructing an empirical production frontier based on the principle of free disposability—a fundamental assumption in production economics (Esteve et al., 2021). This ensures adherence to the axioms of efficiency analysis, making EAT particularly well-suited for benchmarking purposes. Unlike DEA, which assumes a convex production frontier, EAT constructs a non-parametric step-function frontier. This feature is particularly advantageous in the water utility context, where energy consumption does not necessarily follow smooth, continuous patterns. For instance, utilities serving small populations may exhibit abrupt shifts in energy requirements due to infrastructure constraints, treatment intensity, or topographical factors. EAT accommodates these discontinuities by segmenting the input space without enforcing convexity, leading to more accurate benchmarking across heterogeneous water utilities.

Unlike Random Forests and Gradient Boosting methods, EAT is specifically designed to evaluate performance relative to best-practice frontiers, which is essential in our application focused on benchmarking energy efficiency. The EAT approach is based on linear programming (non-parametric) techniques and Classification and Regression Trees (CART) (Breiman et al., 1984). More specifically, the EAT approach uses regression trees, separates observations into regions using different thresholds to measure maximum output (i.e., energy use for the purposes of our study). For instance, it can measure the maximum energy use if the number of customers is higher or lower than a particular threshold. The EAT approach, therefore, imposes the free disposability assumption and adjusts the regression tree to estimate production frontiers and efficiency (Esteve et al., 2023a). To overcome overfitting problems, EAT applies a pruning procedure based upon cross-validation (Esteve et al., 2020; 2021).

Within this context, the main objective of this study is to estimate the energy efficiency in the provision of drinking water services by water companies using the newly developed technique, the EAT. Moreover, energy efficiency scores using DEA and FDH approaches are also estimated. Thus, we compare energy efficiency scores among these non-parametric techniques. Finally, to get a better insight what drives energy efficiency for the provision of water services, bootstrap truncated regression techniques are employed to regress energy efficiency scores against a set of environmental factors related to source of raw water, treatment complexity and population density. This novel piece of work is applied to the water industry in England and Wales over the 2011–2020 period.

This study contributes to the current strand of literature as follows. First, we estimate energy efficiency of drinking water services provided by water companies based on the energy consumed instead of energy costs. This approach allowed us to quantify potential energy savings in physical units, i.e., megawatt hour per year (MWh/year). Second, from a methodological perspective this study uses for the first time a newly developed approach that brings together machine learning and efficiency analysis techniques to accurately measure the energy efficiency of water services. This is a novel approach because, to the best of our knowledge, the EAT approach has not been applied to measure the energy efficiency of drinking water supply processes. Moreover, as we want to better understand how water services can be more energy efficient, we use bootstrap regression techniques to explore the relationship between energy performance and environmental factors.

2. Material and methods

2.1. Methodology to estimate energy efficiency scores

Energy efficiency of water utilities is estimated using the EAT method, which combines regression (decision) trees and efficiency analysis techniques (James et al., 2013; Rebai et al., 2019). The EAT method is used to estimate energy efficiency scores because it overcomes the issue of overfitting that other non-parametric techniques may suffer from. Thus, we use a robust method to generate energy efficiency scores and inform decision-making process. The EAT technique allows measuring energy efficiency scores for each water utility which allows identifying less and more energy efficient units and more importantly, quantifying the energy savings that could be achieved by each water utility. An important methodological advantage of EAT is its ability to model step changes in energy use associated with scale effects and operational heterogeneity. While DEA enforces a convex frontier—thereby assuming smooth substitution between inputs and outputs—EAT's tree-based algorithm detects and preserves discontinuities in the data. This results in a step-function frontier that better reflects the non-linear and non-convex nature of energy use patterns in water utilities, particularly where economies or diseconomies of scale and localized operational practices exist (Sala-Garrido et al., 2025). In other words, EAT offers a closer representation of operational realities in water utilities compared to the smooth, convex frontier imposed by DEA. Water utilities often experience discrete jumps in energy consumption due to infrastructure upgrades, treatment thresholds, or regulatory compliance, which are not well captured by convex approximations. By allowing discontinuities and local splits in the input space, EAT can reflect scale effects and segmentation more accurately. However, this approach is not without limitations. Because the EAT method relies on recursive partitioning, it may be sensitive to data granularity and sample distribution. For instance, sparsely populated regions of the input space may lead to unstable splits or underfitting. Although the pruning and cross-validation steps mitigate overfitting, EAT results can still be influenced by sample size and variable resolution (Guillen et al., 2025).

The starting point of a decision tree under the EAT approach is to use all observations, then advances through intermediate nodes, which break up the dataset. The decision tree finishes at leaves (terminal nodes) which show the estimated output of the production process (energy consumption in our case) (Esteve et al., 2022; 2023a; 2023b). Under the EAT approach, the estimated output is not the average output but the frontier output (i.e., frontier energy consumption in our case). This is because the EAT approach imposes the condition of free disposability, i.e., incorporates production economics theory with decision tree analysis. Furthermore, the efficient frontier that the EAT method constructs is a step frontier which is like the step function frontier constructed by the FDH (Deprins et al., 1984; Esteve et al., 2021).

According to Esteve et al. (2020), the underlying technology produced by EAT meets free disposability and therefore, in our case study, the multi-output EAT method is applied. Let's suppose that the dataset has several predictors defined as $x_1, \cdots, x_m$ with $x_i \in R^m$. These predictors are employed to predict a vector of response variables denoted as $y, \cdots, y_n$ with $y_i \in R^n$. The EAT method selects a predictor variable j and a threshold $s_j \in S_j$ where S_j denotes the set of likely thresholds for the variable j to separate the data into two nodes, t_R and t_L (Esteve et al., 2021). The algorithm employs the sum of the mean squared of error (MSE) to make this split. The mathematical expression is provided below:

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

where n is the sample size; t is the node of the tree (i.e., left and right,t_L and t_R, respectively);$R(t)$ captures the MSE of each node t;$y(t_L)$ and $y(t_R)$ are the estimated output (e.g., energy consumption in this study) for the data in nodes t_L and t_R, respectively (Esteve et al., 2022; 2023a; 2023b). Under the EAT method the estimated outputs are derived as follows:

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

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

where T is the sub-tree that is generated with the EAT method; k denotes the number of splits, $y(I_{T(k|t^* \to t_L, t_R)}(t_L))$ and $y(I_{T(k|t^* \to t_L, t_R)}(t_R))$ is the set of leaf nodes of the tree produced after executing the $k-$ th split that Pareto-dominates node t_L and t_R, respectively (Esteve et al., 2020; 2023a; 2023b).

The Pareto-dominance concept is the contribution of the EAT method to the CART approach in two ways. In particular, the estimated output under the EAT method is the maximum output. Moreover, the data in each node is split based on the free disposability assumption. Finally, the estimated production frontier takes the form of a step function (Esteve et al., 2021).

To avoid any overfitting issues, we use cross-validation techniques to get the best regression (Breiman et al., 1984; Esteve et al., 2023a). Hence, EAT method estimates the following production technology:

$$\widehat{PT_{T_k}} = \{(x, y) \in R^{m+1} : y \le d_{T_k}(x)\} \tag{3}$$

where $d_{T_k}(x)$ is the predictor estimator associated with the sub-tree T_k. Because this study focuses on evaluating energy efficiency of water companies in the provision of drinking water, an input orientation is adopted. It should be noted that water companies cannot define by themselves the number of water connected properties and drinking water demand. The efficiency score under the EAT method is recovered from the following non-parametric (linear programming) model:

$$\varphi^{EAT}(x_k, y_k) = \min\varphi \tag{4}$$

$$subjectto:$$

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

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

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

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

where φ^{EAT} is the efficiency score, $(a^t, d_{T^*}(a^t))$ are points in the input–output space for all $t \in T^*$ where * defines the final sub-tree and λ are intensity variables employed to build the efficient frontier. A unit (water utility in this study) is efficient when its efficiency score is one ($\varphi^{EAT} = 1$).

For comparison purposes, we also estimate energy efficiency scores under two other non-parametric approaches namely: i) FDH and ii) DEA. FDH estimates a step function production frontier, whereas DEA constructs a convex piecewise linear production frontier. The non-parametric method solved to derive the efficiency score under the DEA is as follows:

$$\varphi^{DEA}(x_k, y_k) = \min\varphi \tag{5}$$

$$subjectto:$$

$$\sum_{i=1}^{n}\lambda_i x_{ji} \le \varphi x_{jk}, j = 1, \cdots, m$$

$$\sum_{i=1}^{n}\lambda_i y_{ri} \ge y_{rk}, r = 1, \cdots, p$$

$$\sum_{i=1}^{n}\lambda_i = 1$$

$$\lambda_i \ge 0, i = 1, \cdots, n$$

In the case of FDH method, the model to be solved to estimate energy efficiency for each unit is as follows:

$$\varphi^{FDH}(x_k, y_k) = \min\varphi \tag{6}$$

$$subjectto:$$

$$\sum_{i=1}^{n}\lambda_i x_{ji} \le \varphi x_{jk}, j = 1, \cdots, m$$

$$\sum_{i=1}^{n}\lambda_i y_{ri} \ge y_{rk}, r = 1, \cdots, p$$

$$\sum_{i=1}^{n}\lambda_i = 1$$

$$\lambda_i \in \{0, 1\}, i = 1, \cdots, n$$

2.2. Methodology to identify and quantify variables influencing energy efficiency scores

To better understand factors impacting the energy performance of water utilities, we regress the energy efficiency score obtained from the EAT method against a set of environmental factors that are related to topography, water treatment complexity and density (for more details on these variables please see next section). We use a bootstrap truncated regression developed by Simar and Wilson (2007). We use this approach because the dependent variable takes a value between zero and one. Moreover, the traditional Tobit regression may result in biased estimates because of serial correlation among efficiency scores, error term and environmental variables (Simar and Wilson, 2007). The regression model takes the following form:

$$\varphi_i^{EAT} = \beta_0 + \beta_i \eta_i' + t + \varepsilon_i \tag{7}$$

where φ_i^{EAT} is the energy efficiency score recovered from the EAT method (Eq. (4); β_0 is the constant term; η_i' is the set of environmental variables of any water utility i; t is time and β_i are the parameters that the regression model estimates. Finally, ε_i is the error (noise) term and follows the standard normal distribution.

2.3. Case Study: Data and sample selection

The empirical application conducted in this study focused on evaluating the energy efficiency in the provision of drinking water services by several English and Welsh Water and Sewerage Companies (WaSCs) and Water only Companies (WoCs) over the years 2011–2020. The sample embraces 160 observations being 100 WaSCs and 60 WoCs. Both types of companies operate under private ownership and are natural monopolies. To ensure that customers receive the best quality of service at an affordable price and companies are financially stable to deliver benefits to the environment as well, the regulator is present. Every five years, the Water Services Regulation Authority (Ofwat) determines the future revenue allowance for the sector after reviewing water companies' business plans (price review process). More information about water regulation in England and Wales is available on the webpage of Ofwat.[1]

The selection of the variables to estimate energy efficiency of water companies, i.e., inputs, outputs and environmental variables, was based on past research assessing the performance of water sector in England and Wales and elsewhere (e.g., Berg and Marques, 2011; See, 2015; Pinto et al., 2017; Cetrulo et al., 2019; Goh and See, 2021) and also on statistical data availability for the period evaluated. The response variable (or input) is defined as the energy consumption by water companies measured in MWh per year (Rodríguez-García et al., 2011; Bodik and Kubaska, 2013; Longo et al., 2016; Molinos-Senante et al., 2018; Niu et al., 2019). Two predictor variables (or outputs) are used. The first one is the volume of drinking water delivered measured in megalitres per year (Brea-Solis et al., 2017; Walker et al., 2021). The second predictor variable is the number water connected properties measured in thousands per year (Guerrini et al., 2018; Walker et al., 2019, 2020).

Previous work on the water industry (e.g., Pinto et al., 2017; Molinos-Senante and Maziotis, 2022a; Maziotis and Molinos-Senante, 2022) evidenced that there might be several operating characteristics that could affect the performance of water utilities. As a result, we include the following environmental variables when analysing energy efficiency of water services. To capture the source of raw water, two variables are integrated in the model, i.e., the percentage of water that is taken from rivers and boreholes. Santana et al. (2014) and Molinos-Senante and Sala-Garrido (2017) evidenced that the quality of the raw water influences the energy efficiency of water treatment plants. Hence, the next variables considered in our study are related to water treatment complexity. These are defined as the number of treatment works taken place when water is taken from surface and groundwater (Walker, 2019). We also use the variable "water receiving high levels of treatment" which is defined by Ofwat (2019a, 2019b) as the percentage of water receiving advanced treatment such as activated carbon treatments and pesticide removals. The density variable is defined as the number of population divided by water area and therefore, it is expressed in 000 s/km2 (Sala-Garrido et al., 2021a, 2021b).

To account for temporal effects that could influence the energy efficiency of water companies, the variable "year" is included as a covariate in the bootstrap truncated regression model. The inclusion of this variable aims to capture potential temporal dynamics—such as regulatory adjustments, infrastructure aging, or improvements in operational practices—that may occur throughout the 2011–2020 period. Although time-series or dynamic panel models, such as autoregressive specifications (Lee, 2012), could offer deeper insights into temporal behavior, the structure of the dataset available for this study limits the feasibility of such methods in the current analysis. Instead, the Simar and Wilson (2007) bootstrap truncated regression employed, allows handling bounded dependent variables and accounts for bias and serial correlation in the energy efficiency scores. Future research could extend this work by applying dynamic efficiency models to more richly structured longitudinal datasets.

All data was collected from annual reports by Ofwat and water companies. Although these sources adhere to regulatory standards, the potential for reporting bias and inconsistencies in data collection across utilities cannot be entirely ruled out. To enhance the robustness of future analyses, it is recommended to triangulate self-reported figures with independent sources—such as high-frequency smart meter data or third-party energy audits—which could provide more accurate and objective measurements of energy consumption. Table 1 gathers the descriptive statistics of the variables employed in the study.

3. Results and discussion

3.1. Optimal levels of energy use

Fig. 1 shows the regression tree from the EAT method. It is understood as follows. In each node, the identification number and the number observations are reported. Moreover, it is also shown the predictor that the split was based on the predicted value of the response variable. In our case this is the energy consumption whose predicted value is the frontier value.

According to Fig. 1, it is evidenced that the number of customers of water companies plays an important role on its energy performance. In particular, it was found that on the delivery of drinking water to more than 2.074 million water connected properties requires the frontier use of 561,564 MWh of energy per year. This means that the maximum energy consumption per water connected property is 0.27 MWh/year (561,564 / 2,074,000 = 0.27). For those water companies serving to less than 2.074 million customers, the total energy consumption could be lower but larger per customer. When the number of connected properties is between 885 thousands and 2.074 million the maximum energy consumption could reach the level of 237,212 MWh per year. It means that the maximum energy consumption per property is 268.04 MWh/year. When the number of properties is between 885 and 510 thousands, the frontier energy consumption is estimated at 128,144 MWh per year. This implies that maximum energy consumption per property is 2,388.52 MWh/year. Finally, for those water companies supplying drinking water to less than 510 water connected properties, the maximum use of energy required could be 62,358 MWh per year. Hence, the minimum energy consumption per property is 122.27 MWh/year. Overall, it can be concluded that the levels of maximum use of energy consumption vary depending on the number of connected properties that a water company has. According to past research (Carvalho and Marques, 2016; Guerrini et al., 2018; Walker et al., 2021), economies of scale were found revealing that larger water companies, in terms of water connected properties, are those whose energy consumption per customer could be the lowest.

3.2. Energy efficiency and potential energy savings

The next step of our analysis is to discuss the energy efficiency scores and energy savings potential derived from the EAT approach at water industry level. Table 2 shows that the English and Welsh water industry reported an average energy efficiency of 0.767. This means that on average water companies could cut down energy consumption by 23.3 % while delivering the same level of water to customers. Equivalently, each water company, on average, has the potential to cut down energy use by 63,479 MWh per year.

Looking at the type of water company, i.e., WaSCs and WoCs, on average, WoCs were found to be more energy efficient than WaSCs. The level of energy efficiency over the period of study was 0.709 for an average WaSC and 0.863 for an average WoC. The findings suggest that an average WoC could reduce its energy consumption by 13.7 % while

[1] https://www.ofwat.gov.uk/.

Table 1
Descriptive statistics of the variables to estimate energy efficiency scores of English and Welsh water companies.

Variables	Unit of measurement	Mean	Std. Dev.	Minimum	Maximum
Energy consumption	MWh /year	217,339	146,675	21,971	561,564
Water connected properties	000 s/year	1,578	1,115	279	4,047
Volumes of water delivered	Ml/year	750	548	140	2169
Water taken from rivers	%	24.8	21.2	0.0	73.2
Water taken from boreholes	%	41.8	30.1	0.5	92.1
Number of surface water treatment works	nr	17	15	1	54
Number of groundwater treatment works	nr	53	39	7	127
Water receiving high levels of treatment	%	57.0	22.0	22.0	99.0
Population density	000 s/km2	0.48	0.29	0.15	1.26

Observations: 160.

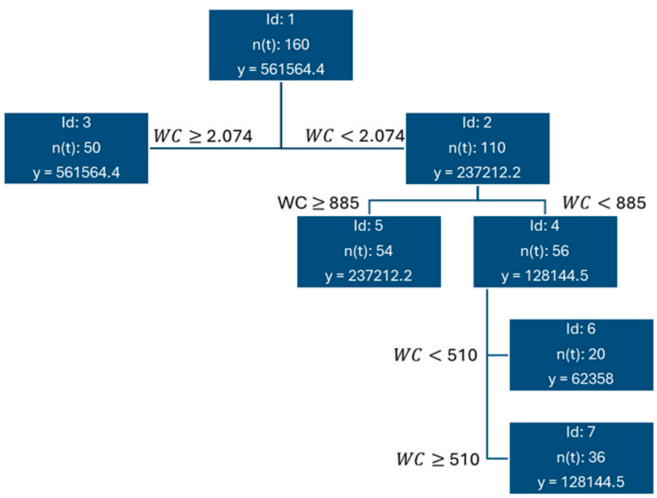

Fig. 1. Regression tree to estimate energy efficiency scores based on Efficiency Analysis Trees method. *where: Id represents the node; n(t) is the number of observations; y is the optimal energy use in MWh/year and WC is the number of water connected properties.*

Table 2
Summary statistics of estimated energy efficiency and energy savings for English and Welsh water companies (2011–2020).

	Energy efficiency score			Potential energy savings (MWh/year)		
	All	WaSCs	WoCs	All	WaSCs	WoCs
Mean	0.767	0.709	0.863	63,479	90,692	22,632
Std. Dev.	0.174	0.165	0.145	72,890	79,259	31,316
Minimum	0.430	0.437	0.581	0	7,381	0
Maximum	1.000	1.000	1.000	270,112	270,112	96,279
Energy efficient units (%)	3.125	3.125	6.667			

maintaining the same level of water output. This is equivalent to a reduction in energy use by 22,632 MWh per year. Higher levels of energy savings were reported for an average WaSC. Thus, the potential savings in energy among WaSCs were at the level of 90,692 MWh per year on average. The results showed that the worst performer among WoCs reported an average energy efficiency of 0.580. The most inefficient company among WaSCs showed a lower energy efficiency, 0.430. This means that the most inefficient companies need to substantially reduce energy consumption to catch-up with the most energy efficient ones in the sector. The worst performer within the WaSC group should cut down energy use by 57 %, whereas the most inefficient WoC should reduce energy consumption by 42 % to deliver the same level of water services. It is also revealed the limited number of energy efficient water companies (3.125 %). Nevertheless, most of the efficient companies are WoCs (6.667 %) whereas only 1 out of 100 WaSCs observations was identified as energy efficient.

While the results (Table 2) indicate that WoCs are, on average, more energy efficient than WaSCs, this observation should be interpreted with caution. The comparison may be confounded by unobserved heterogeneity across companies. Factors such as differences in infrastructure age, geographical conditions, or service area characteristics may influence energy performance but are not explicitly accounted for in the present analysis. The main objective of this study is to benchmark energy efficiency using the EAT methodology rather than to establish causal relationships between company type and energy efficiency. However, alternative methods—such as fixed-effects regression models or propensity score matching—could provide more robust insights by controlling for such confounding variables. Future research could benefit from incorporating these techniques, especially with access to more longitudinal datasets that allow for stronger causal inference.

For comparison purposes, we report the energy efficiency scores derived by the other deterministic approaches, i.e., FDH and DEA. It is found that under the FDH approach, the average energy efficiency was 0.917, whereas under DEA the energy efficiency score was lower, 0.656 (Table 3). There was also a significant difference in the number of water companies being energy efficient. According to Aparicio et al. (2021), the problem of overfitting suffered by DEA and FDH manifests itself in the fact of observing many evaluated units with an efficiency score of one. In other words, the performance assessment is overly optimistic. This conclusion is empirically evidenced in this case study where the lowest percentage of energy efficient water companies was reported for EAT estimations. When efficiency scores were computed based on FDH, a notably larger number of water companies was identified as energy efficient.

The difference in energy efficiency scores between the three approaches is because EAT and FDH estimate a frontier that takes the form of a step function. In contrast, DEA generates a convex piecewise frontier. Differences in energy efficiency estimations also impact the prediction power of FDH reporting bad results (Aparicio et al., 2021). Because one of the objectives of this study is to predict the optimal use of energy in the provision of drinking water, EAT estimations are more suitable for this purpose. The reported divergence in energy efficiency estimations, based on the methodological approach used to compute scores, demonstrates the relevance of using reliable and robust methods to benchmark the performance of water companies. Otherwise, misleading conclusions and therefore, inadequate policy implications might be drawn.

Table 3
Comparison of energy efficiency scores estimated using efficiency analysis trees (EAT), free disposal hull (FDH) and data envelopment analysis (DEA).

Method	Mean	Std. Dev.	Minimum	Maximum	Energy efficient observations (%)
EAT	0.767	0.174	0.430	1.000	3.125
FDH	0.917	0.109	0.657	1.000	31.875
DEA	0.656	0.195	0.346	1.000	8.125

The objective of this study is to evaluate the energy performance of water services using the EAT approach and therefore, the results discussion focuses on the estimated energy efficiency scores from the EAT approach. To get a better understanding of the distribution of energy efficiency over the period of study, Fig. 2 gathers a histogram of the estimated energy efficiency scores. It is found that there were not any cases where energy efficiency score was less than 0.40 on average (2011–2020). Over the years 2011–2020, there were 7 and 11 observations only among WoCs where energy efficiency score was between 0.41 and 0.60 and between 0.61 and 0.80, respectively. In contrast, energy efficiency scores among WaSCs were more symmetric. There were 30 observations related to WaSCs who reported an average energy efficiency score between 0.41 and 0.60. Like WoCs, there were several observations associated with WaSCs where the average energy efficiency was higher than 0.81.

Figs. 3 and 4 report the trend in energy efficiency and potential energy savings based on the type of the company during the years 2011–2020. We also split the results into two sub-periods to link them with the regulatory cycle. The first sub-period, 2011–15 refers to the 2009 price review, whereas the second sub-period, 2016–20 refers to the 2014 price review. We note that during the 2009 price review the water regulator introduced several incentive schemes to incentivise companies to reduce their operational costs. One of these schemes was related to a rolling mechanism on operating costs where the companies were allowed to keep these savings regardless of the period these occurred (Villegas et al., 2019). As part of the 2014 price review, the companies were obliged to bear the risk of any underperformance on expenditure and share with customers any savings from outperformance on expenditure. The results indicated that during the 2011–15 period industry energy performance was at high levels, 0.799. This means that the potential energy savings could reach the level of 20 % which was equivalent to an annual reduction in energy use by 51,356 MWh/year. However, industry energy performance slightly reduced in the following sub-period. It reached the level of 0.773 on average which means that the potential energy savings could be higher and could reach the level of 59,222 MWh/year.

It is shown that energy efficiency for an average WoC was at high levels at the first years of the sample (Fig. 4); 0.918 and 0.914 in 2011 and 2012, respectively. However, a downward trend is reported for the rest of the years. This means that energy efficiency of WoCs deteriorated over time. Average WoC did not manage to maintain the initial high levels of energy standards. In 2011, an average WoC could cut down its energy consumption by less than 8 % to become more efficient. However, the level of energy efficiency dropped to 0.852 in 2015. This means that WoCs could reduce energy use by 96,899 MWh/year to catch-up with the most efficient ones in the industry (Fig. 4). During the period 2011–15 energy efficiency reduced at an annual rate of 1.86 % on average. The potential savings in energy could reach the level of 73,682 MWh/year on average during this period. From 2016 onwards average WoC's energy efficiency continued to go down but at a lower rate. Average energy efficiency reduced to the level of 0.829 in 2020. During the 2016–20 energy could go down by 108,327 MWh/year to deliver the same level of water services.

The evolution over time of energetic performance of WaSCs was similar to the reported levels of WoCs. The results showed that during the first sub-period, average energy efficiency was 0.713 whereas it slightly reduced to 0.706 in the next sub-period. Like WoCs, WaSCs' energy efficiency was at high levels in the first years of study, however, a downward trend was apparent in the following years. During the 2011–15 period, average potential savings in energy for WaSCs were 790,082 MWh/year (Fig. 4). These savings could be considerably higher in the next sub-period because in general energy efficiency scores continued to decline. We noted that in 2020 on average energy efficiency was 0.699 which means that WaSC could further cut down its energy consumption by 30 % to become more efficient. This is equivalent to a substantial saving of 860,175 MWh/year in energy use.

Overall, the results indicated that both WoCs and WaSCs have become less energy efficient over time. Thus, the English and Welsh water companies need to make efforts to improve energy performance. This could have both economic and environmental benefits. For example, annual potential energy savings for 2020 were estimated to be 976,235 MWh/year if English and Welsh water companies were energy efficient. According to the Department of Business, Energy and Industrial Strategy (2021), the mean domestic electricity consumption in Great Britain in 2020 was 3,748 kWh per year per meter. Hence, the estimated potential energy savings from water companies is equivalent to the annual electricity consumed by 260,468 households in Great Britain. Lower energy use could lead to lower energy costs which could lead to savings in operational practices. These operational savings could pass to customers in terms of lower bills. Moreover, the use of less energy would involve a reduction on the greenhouse gas emissions improving therefore, the environmental performance of water companies.

As climate change intensifies hydrological variability and water quality deterioration, water utilities may increasingly rely on energy-

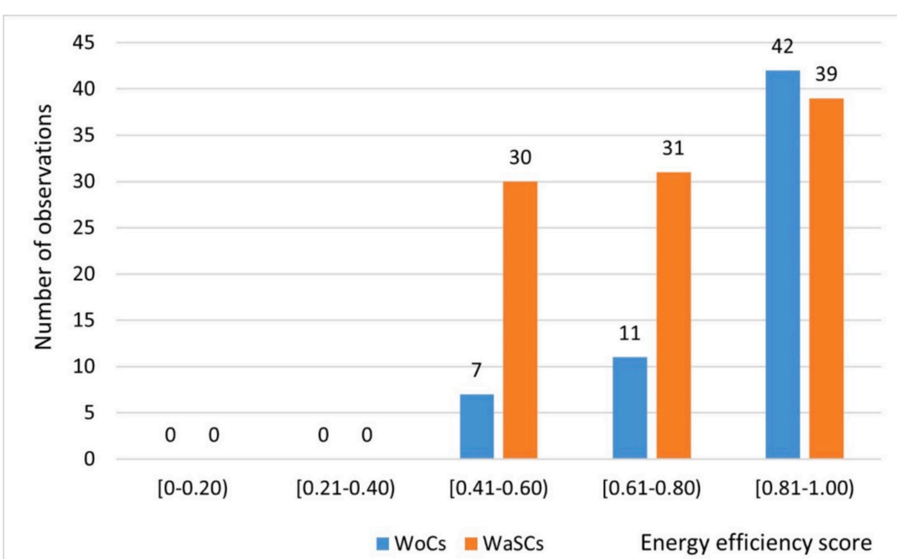

Fig. 2. Histogram of the distribution of energy efficiency scores for English and Welsh water companies (2011–2020).

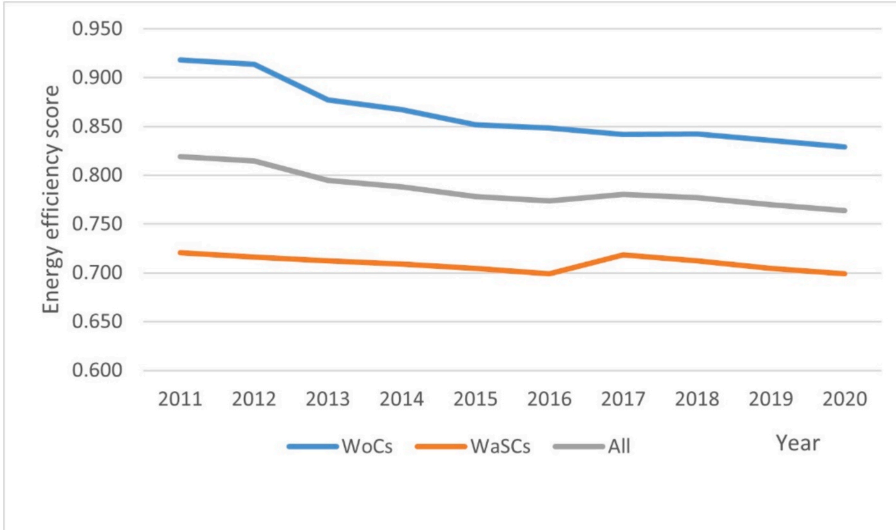

Fig. 3. Temporal evolution of estimated energy efficiency for English and Welsh water companies (2011–2020).

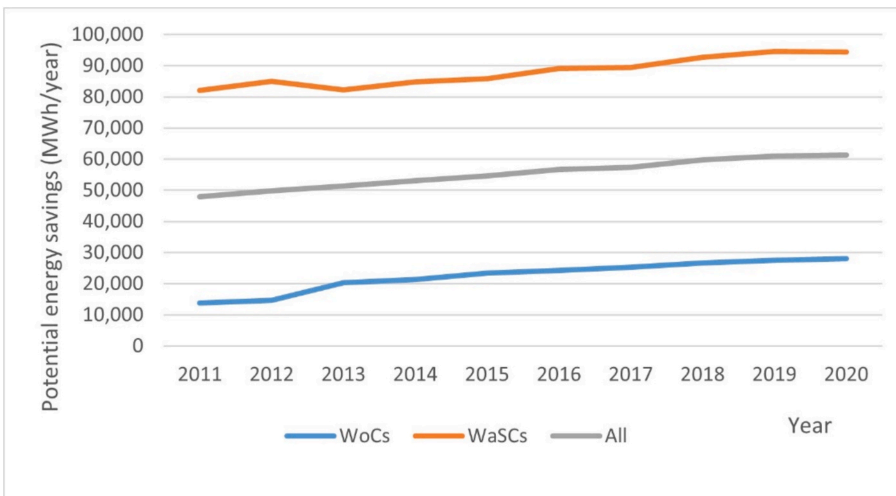

Fig. 4. Temporal evolution of potential energy savings for English and Welsh water companies (2011–2020).

intensive treatment processes to ensure potable water standards. This suggests a potential upward pressure on baseline energy demand to the provision of drinking water in urban settings. However, this trend could be counterbalanced by the adoption of emerging technologies and practices aimed at improving energy performance. For instance, advancements in real-time monitoring, smart water networks, and data-driven decision-making systems are expected to optimize operational processes and reduce unnecessary energy use (Moazeni and Khazaei, 2021; Gu and Sioshansi, 2025). Additionally, greater integration of renewable energy sources, such as solar photovoltaic systems and biogas recovery from wastewater treatment, offers a pathway to decarbonize energy consumption across the water cycle (Kadam et al., 2023; Parraga et al., 2024). Policy and regulatory frameworks will play a pivotal role in guiding these transitions. The increasing emphasis on carbon neutrality and net-zero targets across the water sector—exemplified by initiatives such as Water UK's Net Zero 2030 Routemap—will necessitate comprehensive energy audits, benchmarking, and efficiency interventions (Water UK, 2025). In this context, robust methodologies like the EAT approach used in this study can support utilities and regulators in tracking progress, identifying outliers, and prioritizing investments in energy optimization.

3.3. Factors influencing energy efficiency of water companies

The energetic performance of water companies may be influenced by external factors (environmental variables) which are not under the managerial control of firms. These factors are analysed in Table 4. The results indicate that the higher the proportion of water taken from boreholes and rivers the lower the levels of energy efficiency could be. This could be explained by the fact that the abstraction of more water from these sources could require high levels of energy use putting therefore pressure on energy efficiency. Moreover, the higher the proportion of water receiving higher treatment, the lower the levels of energy efficiency might be. This is because the more complex the treatment of water is, the higher the use of energy would be which could negatively influence energy performance. Furthermore, as population density increases more water may be required to be abstracted, treated and delivered. This could require high levels of energy which could put pressure on energy efficiency. Based on the magnitude of the estimated coefficients, water treatment complexity, density and water abstracted from rivers and boreholes had the major impact on energy efficiency.

Table 4 illustrates that a 1 % increase in the high treatment of water could lead to a decrease in energy efficiency by 0.271 % on average. This

Table 4
External factors influencing energy efficiency of water companies: estimates of bootstrap truncated regression.

Variables	Coefficient	Bootstrap Std. Err.	z-stat	p-value
Constant	5.097	1.062	**4.799**	0.000
% of water taken from boreholes	−0.241	0.090	**−2.684**	0.007
% of water taken from rivers	−0.247	0.091	**−2.716**	0.007
Density	−0.154	0.075	**−2.061**	0.039
Number of treatment works for surface water	−0.003	0.001	**−2.127**	0.033
Number of treatment works for groundwater	−0.002	0.001	**−4.027**	0.000
% of water receiving high treatment	−0.271	0.109	**−2.507**	0.012
Year	−0.011	0.005	**−2.094**	0.036
Sigma	0.152	0.013	**11.890**	0.000
X^2	**77.53**			
p-value	0			

Energy efficiency score is the dependent variable.
Bold indicates that coefficients are statistically significant at 5% significance level.

means that higher levels of treatment require high levels of energy to ensure that water is potable before it is delivered to end users. This result supports the conclusions by Santana (2014) and Molinos-Senante and Sala-Garrido (2017) who evidenced that energy intensity on drinking water treatment facilities is influenced by the quality of raw water to be treated. From a policy perspective, this result confirms the importance of improving the environmental management of watersheds to minimize energy consumption in the provision of drinking water services.

The results showed that treatment works from surface and groundwater sources increase energy consumption (Table 4). The abstraction of water from rivers and boreholes are energy intensive activities which push up energy use and may have a negative impact on performance. Finally, more densely populated areas might require higher levels of water to be delivered to more customers. This could increase energy requirements which might have a negative influence on energy efficiency.

Based on the analysis of energy efficiency and its key determinants across the evaluated water companies, several policy recommendations are proposed to support energy performance improvements and broader decarbonization objectives for the English and Welsh water industry. As a national regulator, OFWAT should develop standardized energy efficiency benchmarks using robust methodologies—such as the EAT approach—tailored to specific asset categories including pumping stations, drinking water treatment plants, and distribution networks. These benchmarks should inform a performance-based regulatory framework, whereby utilities are rewarded for exceeding targets and penalized for underperformance. In addition, OFWAT should mandate comprehensive energy audits covering components such as pump efficiency testing, process energy balances, and the identification of high-consumption assets. These audits should culminate in time-bound action plans, subject to regulatory oversight. Furthermore, OFWAT should require utilities to publicly report annually on key energy metrics, including energy intensity (e.g., kWh/m^3 treated), greenhouse gas (GHG) emissions per unit of service, and progress toward net-zero goals. To accelerate the adoption of digital energy management systems, the regulator could offer co-funding or fast-track approval mechanisms for smart infrastructure investments.

Focusing on water companies, they should be required to formulate detailed energy strategies with measurable targets focused on reducing total electricity consumption, lowering process-level energy intensity, and increasing the share of renewable energy in their supply mix. To enhance operational efficiency, companies should adopt advanced process control systems, including artificial intelligence-based pump scheduling, variable frequency drives, and SCADA-integrated energy dashboards. Regular training in energy-efficient practices for operational staff can help foster a culture of continuous improvement. In addition, water companies should pilot and scale up emerging low-energy technologies with demonstrated success. The integration of energy key performance indicators (KPIs) into capital expenditure planning and asset management strategies is essential to embed energy efficiency as a core operational priority.

From a water resources management perspective, the significant influence of water quality on energy performance highlights the importance of integrated water resource management. Policies aimed at improving upstream water quality can substantially reduce the need for energy-intensive downstream treatments. Key measures include the enforcement of stricter controls on agricultural runoff—such as vegetated buffer zones along waterways and limitations on fertilizer and pesticide use near catchment areas. Complementary to this, green infrastructure solutions—such as constructed wetlands, riparian buffers, and sustainable drainage systems—can serve as effective pre-treatment buffers by intercepting and filtering pollutants before they enter raw water sources (Mmachaka et al., 2023). Advancing integrated catchment management and land-use planning that explicitly prioritizes water quality protection (Cerutti et al., 2019) will further reduce the energy burden of treatment processes. Collectively, these strategies promote both environmental sustainability and enhanced energy efficiency in the delivery of drinking water services.

4. Conclusions

The move to a sustainable water industry from an economic and environmental perspective requires the assessment of energy efficiency of water services. Understanding the levels of energy efficiency and how it evolves over time can help regulators and companies to make informed decisions. In doing so, it is fundamental to use reliable and robust approaches to avoid misleading conclusions. Traditionally, the assessment of performance in the water industry was conducted using linear programming methods such as DEA and FDH. These approaches could suffer from over-optimistic efficiency scores due to small sample size potentially generating less reliable results. To overcome this issue, this study uses the EAT method to estimate energy efficiency scores of a sample of water companies based on the energy consumed by them.

The main findings can be summarized as follows. The average energy efficiency of the English and Welsh water industry for the 2011–2020 period was 0.767. This means that on average water companies could save 23.3 % of their energy consumption if they were energy efficient. Based on the energy used by water companies, on average they could save 63,479 MWh/year. On average, energy efficiency of WoCs was 0.863 and potential energy savings were estimated at 22,632 MWh/year. By contrast, the average energy efficiency of WaSCs was 0.709 which involves 90,692 MWh/year as potential energy savings. The results from the bootstrapped truncated regression showed that water treatment complexity, source of raw water and population density were the main factors that affected energy performance.

Based on the results of energy efficiency assessment, policy makers could identify how well water companies are doing in terms of energy performance and how much energy needs to be saved so that water services are provided in an efficient and sustainable way. Our results showed that industry's energy performance deteriorated over time and a more efficient use of energy is recommended. It has also evidenced that the higher level of water treatment could lead to higher levels of energy consumption. There are several reasons behind the need of using advanced levels of treatment to produce drinking water. In the last years, the drinking water supply regulations in England and Wales have been amended several times establishing more restrictive thresholds for different pollutants (DWI, 2023). Moreover, river quality in catchments with intensive agriculture is likely to remain worse now than before the 1960 s (Whelan et al., 2022) which involves advanced water treatment process to produce potable water. Hence, improving the quality of the natural water bodies, i.e., raw water, for example, banning water discharges into them will generate positive impacts from an economic and environmental perspective.

Building upon the methodological and empirical contributions of this study, several avenues for future research are proposed to further advance the understanding of energy efficiency assessments in the water sector. One promising direction involves linking energy efficiency scores with GHG emissions, enabling a joint evaluation of energy and environmental performance. Such integration would enhance the usefulness of efficiency assessments for supporting the development of decarbonization strategies. In addition to estimate energy savings, future studies should also incorporate economic dimensions—such as cost-effectiveness or life cycle costs—thereby facilitating a more comprehensive framework for evaluating and prioritizing investments in infrastructure modernization. While this study examines the influence of selected exogenous variables on the energy efficiency of water companies, further research could expand this analysis to include additional factors, such as the age of infrastructure, the integration of renewable energy systems, and the adoption of digital technologies. Including such variables would provide deeper insights into the drivers of energy performance and support more informed policy and management decisions in the water sector. Finally, alternative methods—such as fixed-effects regression models or propensity score matching—could be employed to better isolate the effects of organizational structure, infrastructure age, and geographical conditions on energy efficiency. These approaches would enable more robust causal inference between energy efficiency scores and the key characteristics of WoCs and WaSCs.

CRediT authorship contribution statement

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

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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.

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