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Assessing the influence of environmental variables on energy efficiency changes in the provision of drinking water services

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Within the context of the water-energy nexus in drinking water provision, it is crucial to evaluate temporal shifts in energy efficiency. Utilizing the Stochastic Nonparametric Envelopment of Data (StoNED) approach, this research estimates longitudinal variations in the energy efficiency of drinking water services integrating multiple environmental variables. The analysis, conducted in England and Wales from 2008 to 2020, indicates that the source and quality of raw water, as well as population density, influenced the energy performance of water utilities. Quantitative findings evidenced marked disparity in energy efficiency among different companies, with an average efficiency of 0.617 and a range from 0.437 to 0.944. The dynamic assessment indicates an average annual enhancement of 1.1% in the sector, predominantly propelled by technical advancements (0.9%) rather than by improvements in efficiency (0.2%). This study emphasizes the critical need for bespoke policies and incentives to boost energy efficiency and support sustainable urban water management.

Water and energy resources are inherently linked, a relationship that is expected to intensify due to population growth, economic development, and climate change impacts[1,2]. The imperative of using energy sustainably while progressing in the provision of clean and affordable water aligns with key Sustainable Development Goals set by the United Nations[3]. A sustainable approach to energy use in drinking water provision not only has the potential to reduce production costs, thereby lowering consumer tariffs, but also plays a crucial role in reducing greenhouse gas (GHG) emissions[4]. Consequently, understanding the factors that influence energy consumption and identifying pathways towards its efficient use are of paramount importance for researchers and policymakers.

To enhance the understanding of the water-energy nexus within the urban water cycle, extensive research has been conducted. Several past studies have focused on quantifying energy consumption in drinking water provision and estimating the potential increase in energy demand driven by socio-economic and demographic factors[5–8]. Additionally, research has been conducted to identify potential energy savings across the water supply chain[9–11]. Alternative studies have focused on assessing the environmental impacts of the provision of drinking water by using life cycle analysis tools[12,13]. Despite these significant contributions, there remains a gap in these studies regarding the evaluation of energy efficiency (EE) in the provision of drinking water. EE is a synthetic index and therefore, incorporates multiple variables (inputs and outputs) into the assessment. Within the urban water sector, EE is related to the potential for reducing energy usage by water companies without compromising the volume and quality of drinking water supplied[14–16].

The concept of EE in the drinking water sector has explored at the treatment plant level, i.e., for facilities processing raw water into potable water[16,17]. However, the provision of drinking water encompasses other stages (abstraction of raw water from natural sources and distribution of treated water to consumers) which should be considered when assessing EE in the drinking water sector. Research on the EE of the complete drinking water provision process has been limited but has included noteworthy contributions. Ananda[14] conducted a pioneering study that assessed the EE of 49 water companies in Australia. This study also estimated their energy productivity (EP), which tracks changes in energy performance over time, providing insights into the dynamic nature of energy use within the sector. It employed Data Envelopment Analysis (DEA) method for both EE and EP estimations. It is a non-parametric technique that does not require a pre-determined functional form of the production technology, making it adaptable to various operational data. However, DEA's deterministic nature limits its ability to incorporate potential environmental variables that might affect energy performance. Addressing these methodological limitations, Molinos-Senante and Maziotis[16] advanced the research by applying artificial neural networks to estimate the EE of water companies in England and Wales. ANNs are capable of identifying complex, non-linear relationships

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between inputs and outputs, thus providing a more nuanced understanding of EE. Despite this methodological enhancement, their study focused primarily on assessing annual EE without delving into the temporal changes in energy performance, which are crucial for understanding trends and making strategic improvements.

Overall, while past research has made significant strides in assessing energy performance at different stages of water provision, there remains a gap in comprehensively understanding and analyzing the changes in energy performance over time across the entire water supply chain. Addressing this gap is essential for developing targeted strategies to improve energy performance in the water sector, ultimately leading to reduced environmental impacts and enhanced sustainability. The main aim of this study is to evaluate the changes in energy performance within the drinking water sector by calculating EE and EP metrics, employing an innovative methodological approach that incorporates environmental variables into the synthetic indicator's computation. This analysis progresses by breaking down EP into two distinct components: energy efficiency change (EEC) and energy technical change (ETC). The introduction of this novel methodology is essential for a deeper understanding of the determinants affecting the energy performance of water companies. By integrating environmental variables, the approach not only captures the direct inputs and outputs traditionally associated with energy performance but also considers broader variables that could influence these metrics. Furthermore, by distinguishing between EEC and ETC, the study provides clarity on whether improvements in energy performance are due to enhanced efficiency practices or are attributable to technological advancements. This distinction is crucial for identifying targeted strategies that could lead to significant reductions in energy consumption within the sector. The estimation of the EE for each water company evaluated also allowed to estimate potential energy savings if they were energy efficient.

Table 1 | Estimates of the energy frontier function

Variables	Mean	Median	Min	Max
Water delivered	0.875	0.88	0.81	0.92
Water connected properties	0.135	0.15	0.09	0.33
Population density	0.038	0.043	0.02	0.08
Percentage of surface water	−0.022	−0.01	−0.05	0.05
Percentage of groundwater	0.019	0.022	0.01	0.07
Number of surface water treatmet works	0.035	0.045	0.01	0.08
Number of groundwater treatmet works	0.099	0.21	0.04	0.41
Water receiving high quality of treatment	0.097	0.011	0.05	0.31
Time	−0.002	0.001	−0.004	0.004

Results and Discussion

Energy efficiency assessment

The first step in assessing the EE of each water company was to estimate the energy frontier function using the Stochastic Nonparametric Envelopment of Data (StoNED) method. Python software was used for all estimations in the study. The sum of coefficients of both variables (volume of water delivered and number of water connected properties) are close to 1, indicating that on average water companies operate under constant returns to scale. On average, a 1% increase in the volume of water delivered and in the number of water connected properties could lead to an increase in energy use by 0.875% and 0.135%, respectively.

The number of treatment works undertaken when water is sourced from groundwater and the percentage of water receiving high-quality treatment are the variables most affecting energy use, according to the magnitude of their average values (Table 1). This is consistent with findings by Molinos-Senante and Maziotis[16], who, using random forest regression, concluded that the complexity and extent of treatment processes significantly impact energy consumption in water companies. Population density has also been identified as a relevant variable affecting energy use by water companies. On average, a 1% increase in population density could require a 0.038% increase in energy requirements, revealing noticeable economies of density. The variable 'time' had a negative sign, implying that on average, over time, water utilities have reduced their energy requirements. This underscores the importance of conducting longitudinal analysis of energetic performance of water companies.

The main statistics of the EE for the entire water industry, and by type of company, are depicted in Fig. 1. The mean EE for the 288 observations was 0.617, indicating that, on average, water companies could reduce their energy use by 46.3% to provide the same volume of drinking water and number of properties if they operated at full energy efficiency. EE scores varied between 0.437 and 0.944, demonstrating significant differences among water companies. This finding reveals the need of adopting tailored strategies to enhance EE in the water sector. It is also noteworthy that none of the evaluated water companies achieved the maximum EE score of 1.0, indicating none were fully energy efficient. Estimations based on the StoNED method yielded slightly higher EE scores than those reported by Molinos-Senante and Maziotis[16] using artificial neural networks and DEA, which were 0.411 and 0.436, respectively. This discrepancy underscores the importance of employing adequate and robust methods for assessing energetic performance in the water industry—and potentially other industries—to avoid biased conclusions.

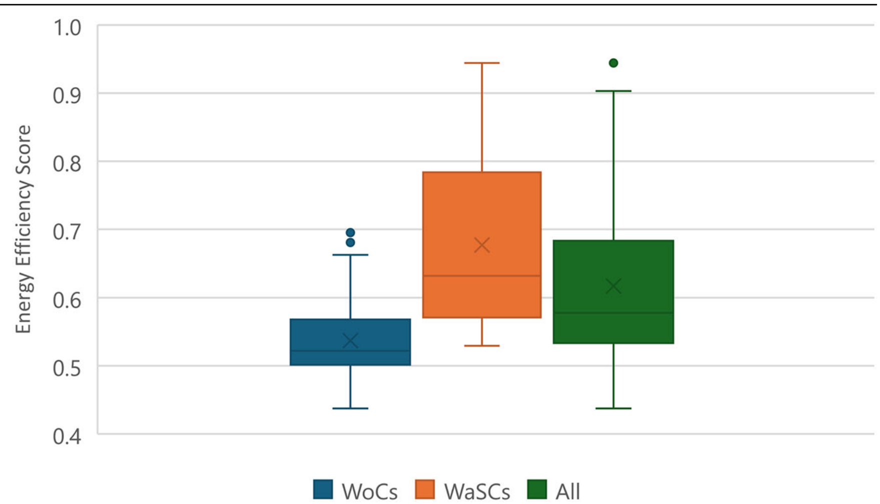


Fig. 1 | Statistics of energy efficiency scores for assessed water companies for 2008–2020. Blue color refers to water only companies (WoCs), orange color to water and sewerage companies (WaSCs) while green color integrates both water only companies and water and sewerage companies. Lower error bars corresponds to the 25th percentile, while the upper error bars corresponds to the 75th percentile. The solid line inside the box refers to the 50th percentile while the cross is the median. The points correspond to outliers.

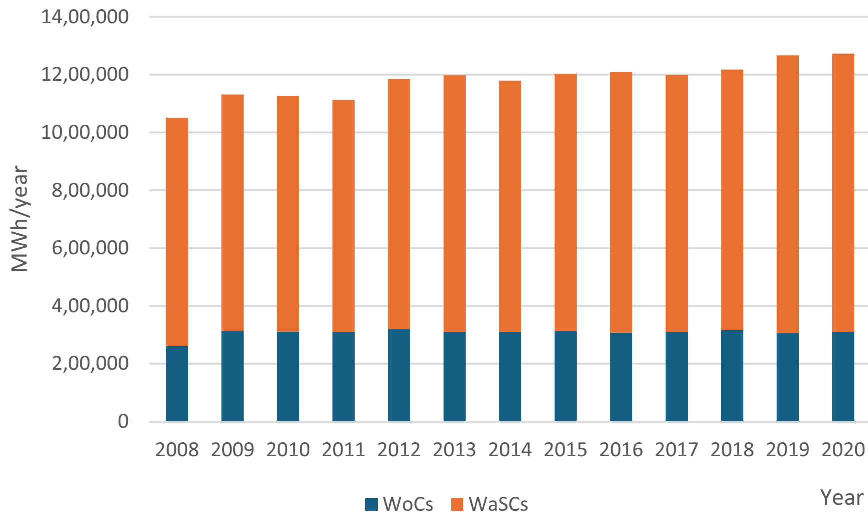


Fig. 2 | Evolution of total potential energy savings of water companies if they were efficient from 2008 to 2020. Blue color refers to water only companies (WoCs) while orange color to water and sewerage companies (WaSCs).

Delving into the results by type of water company, it was found that on average, water and sewerage companies (WaSCs) were more energy efficient than water only companies (WoCs). The mean EE for WaSCs was 0.677, while for WoCs it was 0.537. This implies potential average energy savings of 32.3% for WaSCs and 46.3% for WoCs, respectively, to achieve the same level of water delivered and number of connected properties. The differences in EE between the two types of water companies were statistically significant, as indicated by a p-value of <0.05 from the Mann-Whitney test Mann-Whitney is a non-parametric test that is used to compare two sample means that come from the same population, and used to test whether two sample means are equal or not[18]. From a policy perspective, the results from this study highlight the necessity of setting specific EE targets for each water company that take into account their structural characteristics.

Within each group of water companies, WoCs exhibit greater homogeneity in terms of EE as evidenced by the estimated standard deviation of EE scores, which was 0.061. The EE scores for WoCs ranged from a minimum of 0.437 to a maximum of 0.695. By contrast, WaSCs showed greater variability in their EE scores, with an estimated standard deviation of 0.109 and EE scores ranging from 0.529 to 0.944. Given the narrower range of EE scores among WoCs, policy measures could focus on setting higher baseline efficiency standards for this type of water companies while allowing more flexible standards for WaSCs to achieve comparable improvements. Moreover, considering the diversity in performance among WaSCs, customized support programs can be developed to address specific EE challenges faced by these companies. In this context, potential future research could involve estimating the EE of English and Welsh water companies using a metafrontier StoNED framework. This approach would enable the exploration of how economies of scale and scope impact the performance of WaSCs and WoCs. Such a study would provide valuable insights into the differential efficiencies driven by varying operational scopes and scales within the industry.

Potential energy savings were estimated based on current energy use and EE score computed for each water company (Eq. 7). Figure 2 indicates that potential energy savings in the provision of drinking water have slightly increased over the years, from 1,051,074 MWh/year in 2008 to 1,277,530 MWh/year in 2020, representing a 21% rise. The potential savings attributed to WaSCs account for approximately 75% of the total, due to their larger size in terms of the volume of water delivered and the number of properties supplied.

Table 2 illustrates changes in the average EE and energy use of the assessed water companies from 2008 to 2020. It reveals that estimated EE scores varied, with a maximum of 0.641 in 2008 and a decrease to 0.599 in 2015. Moreover, the average energy consumption by these water companies also showed fluctuations over the years, recording a minimum of 189,288 MWh/year in 2013 and peaking at 223,062 MWh/year in 2019. Overall, despite improvements in EE, these were counterbalanced by increases in energy consumption, leading to a rise in potential energy savings.

Table 2 | Evolution of average energy efficiency (EE) and energy use of the water companies in England and Wales

Year	Average EE	Average Energy use (MWh/year)
2008	0.641	196,421
2009	0.632	195,216
2010	0.634	193,734
2011	0.635	193,135
2012	0.620	198,779
2013	0.601	189,288
2014	0.607	191,338
2015	0.599	190,877
2016	0.600	193,885
2017	0.616	208,795
2018	0.617	212,705
2019	0.613	223,062
2020	0.607	221,027

The consistent rise in potential energy savings over the years suggests that ongoing investment in EE is both necessary and potentially beneficial. For regulators and policymakers, the increasing potential for energy savings calls for the formulation of stricter energy efficiency targets and regulations. Policies could be designed to incentivize all water companies, especially larger ones like WaSCs, to adopt more advanced energy-saving technologies and management practices.

Energy used by water companies in England and Wales primarily comes in the form of electricity. Therefore, using the GHG emission conversion factors for electricity in the United Kingdom GHG emission conversion factors expressed in $KgCO_2$ equivalent per kWh: 2008: 0.49608; 2009: 0.49381; 2010: 0.48531; 2011: 0.45205; 2012: 0.46002; 2013: 0.44548; 2014: 0.49426; 2015: 0.46219; 2016: 0.41205; 2017: 0.35156; 2018: 0.28307; 2019: 0.25560; 2020: 0.23314[19] for each year, it was estimated the potential GHG emission savings associated with energy savings in the provision of water services (Fig. 3). This approach aligns EE with environmental performance by quantifying how reductions in energy consumption could lead to lower carbon emissions.

The trend in potential reduction in GHG emissions from water companies in England and Wales (Fig. 3) contrasts with the trend in energy

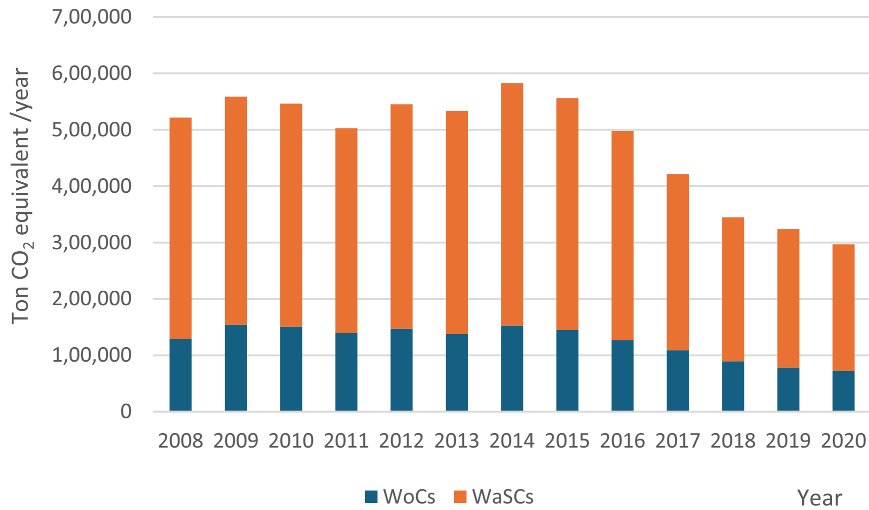


Fig. 3 | Evolution of potential reduction in greenhouse gas emissions from 2008 to 2020 of English and Welsh water companies. Blue color refers to only companies (WoCs) while orange color to water and sewerage companies (WasCs).

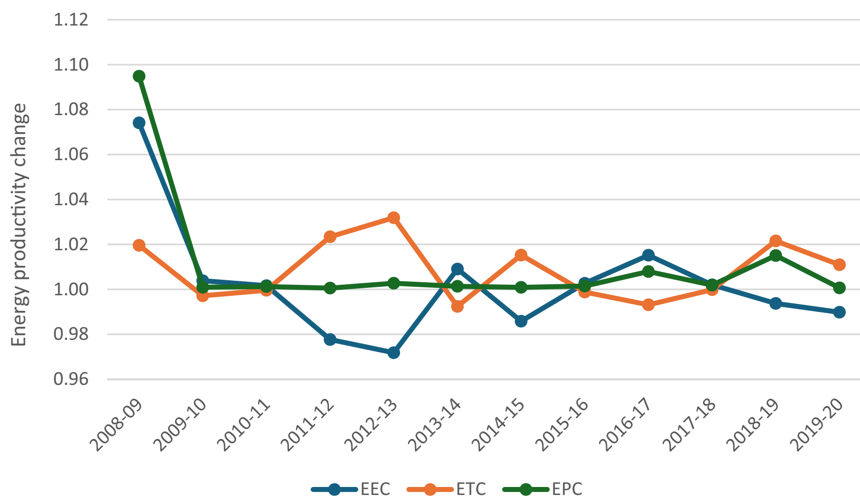


Fig. 4 | Evolution of changes in energy performance of English and Welsh water companies from 2008 to 2020. Green color represents energy productivity change (EPC), blue color represents energy efficiency change (EEC) while orange color represents energy technical change (ETC).

savings (Fig. 2) due to the decarbonization of electricity production in the United Kingdom. While potential energy savings have increased over the years, potential reductions in GHG emissions have notably been decreasing since 2016. This reduction is primarily driven by significant changes in the energy sector, specifically the shift towards less carbon-intensive energy sources for electricity production. The GHG emission conversion factors reflect this transition, with the maximum factor recorded in 2008 (0.49608 Kg CO_{2e}/year), when electricity production was more reliant on fossil fuels[19]. Conversely, the minimum conversion factor in 2020 (0.23314 Kg CO_{2e}/year)[19] indicates a cleaner electricity grid, utilizing more renewable sources and less carbon-intensive technologies. This shift not only impacts the indirect GHG emissions from water companies but also enhances the overall environmental benefits of energy savings in the water sector. Such trends underscore the importance of aligning EE measures with broader national goals for decarbonization, as reductions in energy use in water services now yield greater benefits in terms of GHG emission reductions than they would have a decade ago. This alignment can play a crucial role in meeting national and international carbon reduction targets.

Energy productivity assessment

The analysis of changes in the energetic performance over the years, as depicted in Fig. 4, indicates that the English and Welsh water industry has experienced modest improvements in its EP. On average, EP increased at an annual rate of 1.1%, attributed to both EEC and ETC. On average, gains in efficiency were small at the level of 0.2% per year. This suggests that less energy-efficient companies have been making incremental efforts to enhance their efficiency, potentially closing the gap with the more energy-efficient companies in the industry. Such efforts could include adopting best practices, improving operational processes, or investing in energy-efficient technologies. Moreover, the rate of technical progress contributing to EP was higher, at 0.9% per year. This indicates that the industry is not just improving its existing practices but is also adopting new technologies and methods that contribute to overall technical improvements. This trend of technological leadership, albeit at a modest rate, suggests a positive direction towards more innovative and sustainable water management practices.

To connect the EP results with the regulatory cycle, the study period was divided into three sub-periods: 2008–2010, 2011–2015, and 2016–2020. Each sub-period reflects different regulatory environments influenced by periodic price reviews conducted by the regulator. The sub-period of 2008–2010 encompasses the outcomes of the 2004 price review, during which the regulator implemented several incentive schemes aimed at improving the performance of the water industry. Water companies were allowed to retain any savings in operating expenditure they achieved, irrespective of the year these savings were made. This policy was intended to encourage water companies to find cost-effective solutions and efficiencies that would benefit both their operations and their customers over the long term. Additionally, the regulator introduced financial rewards and penalties tied to service quality improvements. This was facilitated through the

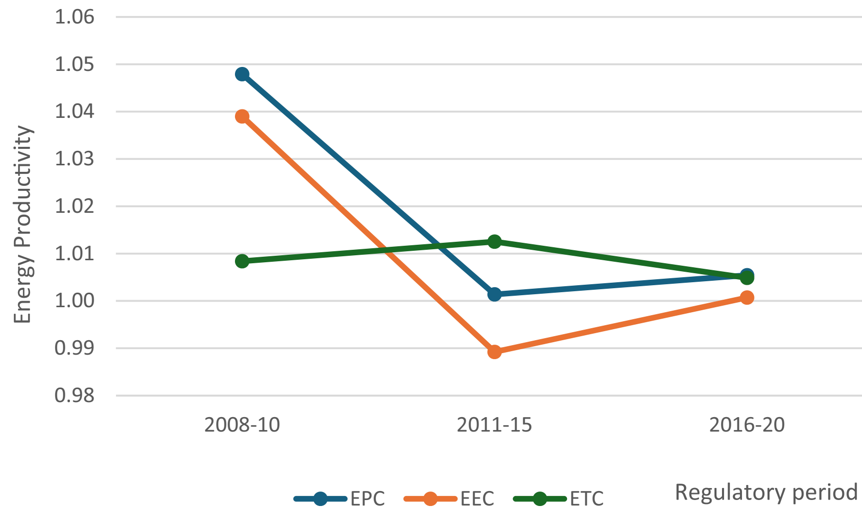


Fig. 5 | Evolution of changes in energy performance of English and Welsh water companies according to regulatory periods. Blue color represents energy productivity change (EPC), orange color represents energy efficiency change (EEC) while green color represents energy technical change (ETC).

Overall Performance Assessment (OPA) framework[20]. During the period from 2008 to 2010, the EP of water companies improved by 4.8%, which was primarily driven by an increase in EEC of 3.8%, while ETC contributed only 0.8%. This indicates that the improvement in EP was largely due to the companies moving closer to the efficient frontier, rather than a positive shift in the frontier itself.

During the 2011–2015 sub-period, which followed the 2009 price review, regulatory strategies continued to emphasize cost-efficiency but with an adjusted focus that included sharing any savings in infrastructure maintenance between utilities and customers. This was an extension of the previous period's rolling incentive concerning operating expenditures. However, the OPA framework was discontinued and replaced with the Service Incentive Mechanism (SIM), which specifically targeted improvements in customer service. The results from this sub-period demonstrate that the EP of the water industry remained largely stable, with a negligible average increase of 0.01%. A notable shift occurred in the contributions of the components of EP: EEC regressed, contributing negatively to EP with an average decrease of 1.38% per year, whereas ETC saw an annual increase of 1.3%. The negative contribution from EEC during this period suggests that, despite regulatory incentives aimed at enhancing operational efficiency, there might have been challenges or inefficiencies that prevented EE improvements.

During the last sub-period (2016–2020), which followed the 2014 price review, the regulator implemented a new framework that further refined the focus on service quality and environmental performance within the water industry. This period was marked by the introduction of common performance commitment indicators, alongside Outcome Delivery Incentives (ODIs). These ODIs were designed to financially reward utilities for outperforming set targets and penalize them for underperformance, thus strongly incentivizing the delivery of promised outcomes. The results from this sub-period reveal that the EP of the industry increased by an average of 0.5% per year, driven primarily by improvements in ETC, which also saw an increase of approximately 0.48% per year. In contrast, EEC remained almost constant, with a negligible average increase of 0.07% per year.

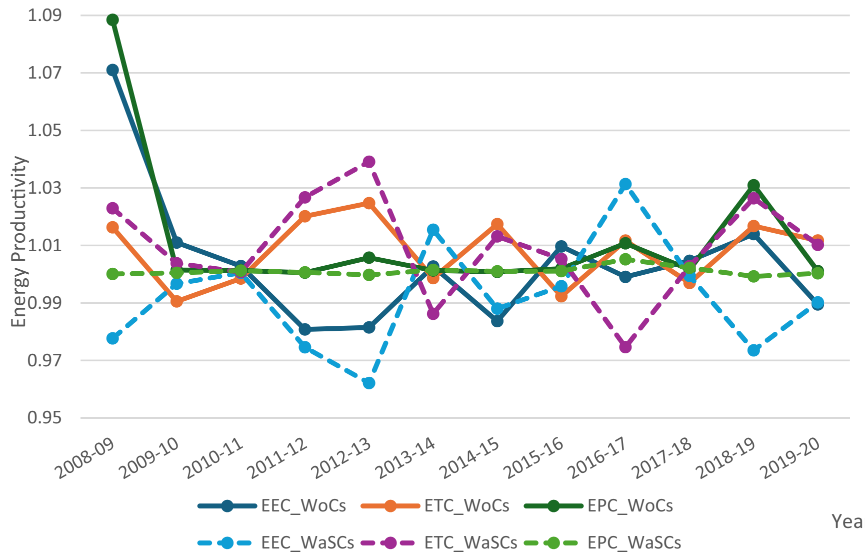
The overall results evidenced that after 2010, despite the regulatory incentives aimed at improving performance, gains in EE were minimal. This could be due to several factors, such as already achieving near-optimal levels of EE, diminishing returns on new efficiency measures, or perhaps a greater regulatory and industry focus on achieving broader environmental and service quality outcomes rather than specific EE improvements Fig. 5. Moreover, the limited contribution from ETC to EPC for the three sub-periods assessed indicates that there were minimal advancements in technology or significant innovations across years that would constitute a structural change in how water companies manage or use energy. Instead, the predominant driver of improved performance appears to be internal optimizations and enhancements within existing frameworks and technologies.

Figure 6 compares the changes in energy performance of WaSCs and WoCs over the years, highlighting that WoCs were generally more energy productive than WaSCs. Both types of companies made strides to adopt the industry's best practices; however, the effect of EE on EP varied significantly between them. WoCs realized slight improvements in EE, resulting in an average annual EP improvement of 2.1%, with EE contributing 1.2% to this gain. Additionally, ETC had a smaller, yet positive, influence on EP, with a technical progress rate of 0.8% per year. These results suggest that WoCs were proactive in managing energy usage and aligned with the most energy-efficient utilities by adopting top industry technologies. In contrast, WaSCs showed an average annual EP growth of only 0.1%, primarily driven by technical progress at a rate of 0.9% per year. Despite this, the technical advancements were insufficient to enhance the average productivity of WaSCs, as losses in EE occurred at a rate of 0.8% per year. This indicates that during the study period, the average WaSC failed to improve its EE, which adversely affected its EP.

Analyzing the trend in EP of WoCs, it is observed that from 2009 to 2011, gains in EE were the primary drivers of productivity improvements. In the years following, WoCs continued to enhance their EE, albeit at a reduced pace. From 2012 to 2015, a decline in EE was apparent, indicating that less energy-efficient WoCs faced challenges in managing energy consumption relative to the level of water services provided. The improvements in EP during this period were largely attributed to the adoption of advanced technologies, with technical progress advancing at an average annual rate of 1.5%. This technical progression persisted until the final years covered by the sample. Conversely, the EP of WaSCs remained largely stable and positive throughout the study period, though the increases in productivity were modest. Between 2009 and 2013, WaSCs exhibited some degree of technological leadership, yet this was insufficient for marked performance enhancement. The inability of these utilities to effectively manage energy use in day-to-day operations resulted in significant losses in EE. These efficiency losses persisted throughout the study period, except for brief improvements during the 2013-14 and 2016-17 intervals. Consequently, any benefits from technical advancements were negated by declines in EE, preventing the EP from rising above an annual average of 0.5%.

From a policy perspective, given the variability in EP over the years, continuous monitoring of it should be mandated. This would ensure that both WaSCs and WoCs remain committed to improving their energy performance. Regular audits and feedback loops could be institutionalized to foster continuous improvement. Moreover, the fluctuation in EE improvements, especially in WoCs between 2009 and 2015, suggests that

Fig. 6 | Evolution of changes in energy performance of English and Welsh water companies from 2008 to 2020 grouped by types of water companies. Continuous lines refer to water only companies (WoCs) being lines in blue color the energy efficiency change (EEC_WoCs), orange lines to energy technical change (ETC_WoCs) and green lines to energy productivity change (EPC_WoCs). Discontinuous lines refer to water and sewerage companies (WaSCs) being lines in blue color the energy efficiency change (EEC_WaSCs), purple lines to energy technical change (ETC_WaSCs) and green lines to energy productivity change (EPC_WaSCs).



short-term gains may not be sustainable without continual investment in infrastructure. Policies encouraging long-term investment in sustainable and energy-efficient water infrastructure could be beneficial in the long term.

Methods

The evaluation of energy performance of water companies involves estimating two crucial synthetic indicators, EE and EP, utilizing the StoNED method developed by Kuosmanen and Kortelainen[21]. This method represents a synthesis of non-parametric (linear programming) and parametric (econometric) approaches. It uniquely incorporates a stochastic noise term into a non-parametric DEA-style efficiency frontier, which accounts for both inefficiency and stochastic noise, aligning it with parametric frameworks[22]. StoNED, like DEA, operates without assumptions regarding the production function's functional form, maintaining critical properties such as convexity, monotonicity, and returns to scale, as established in the DEA methodology[23]. A significant advantage of the StoNED method over traditional DEA is its capacity to handle heterogeneity among water companies by including environmental variables[24].

The process of evaluating energy performance using StoNED begins with the estimation of EE scores, followed by the determination of EP scores. Each stage involves specific procedures which are described as follows.

Energy efficiency estimation

The estimation of the EE for each water company involves several stages, described as follows:

Stage 1. Definition and estimation of the energy frontier function:

The energy frontier function relates the energy consumption of the assessed water companies with their outputs (volume of drinking water and number of water connected properties) along with other environmental variables:

$$EN_{i,t} = f\left(y_{i,t}, z_{i,t}\right) + \varepsilon_{i,t} \quad (1)$$

where f represents function, EN is the energy consumption, i represents the water company at any time t, y represents a set of outputs produced by water companies and, z is a set of environmental variables that could influence the energy consumption of the water services. Finally, the term $\varepsilon_i t$ is the composite error term of the frontier model. It consists of two components, inefficiency, $u_{i,t}$, and noise, $v_{i,t}$. Inefficiency follows the normal distribution and noise follows the standard normal distribution[21]. In other words, $\nu_{i,t} \sim N\left(0, \sigma_\nu^2\right)$ and $u_{i,t} \sim N^+\left(0, \sigma_u^2\right)$, where σ_ν^2 and σ_u^2 are the variance of noise and inefficiency, respectively. The expected value of inefficiency is defined by $E(u) = \mu$ and is directionally proportional to the parameter $\sigma_u : \mu = \sigma_u\sqrt{2/\pi}$ where σ_u is the standard deviation of inefficiency. Furthermore, parameters α, β and γ are recovered after the estimation of the energy frontier model in Eq. (1).

The energy function frontier is estimated by solving the following non-linear programming model using convex nonparametric least squares approach[24]:

$$\min \sum_{i=1}^{I}\sum_{t=1}^{T}\varepsilon_{i,t}^2 \quad (2)$$

subject to:

$$lnEN_{i,t} = ln\left(\alpha_{i,t} + \beta_{i,t}y_{i,t}\right) + \gamma z_{i,t} + \varepsilon_{i,t} \; i = 1,..,I; t = 1,\ldots,T$$

$$a_{i,t} + \beta_{i,t}y_{i,t} \geq \alpha_{j,w} + \beta_{j,w}y_{j,w} \; i,j = 1,\ldots,I; t,w = 1,\ldots,T$$

$$\beta_{i,t} \geq 0 \; i = 1,..,I; t = 1,\ldots,T$$

In Model (2), the β coefficients are interpreted as marginal products[25]. The constant term α captures the scale of operations of water services. In this study, it was set $a_{i,t} = 0$ because water companies operate under constant returns to scale, i.e., at the most productive scale size[17]. The second constraint in Model (2) guarantees that the energy function is convex and the last constraint ensures monotonicity in outputs[23,26].

Stage 2. Estimation of energy efficiency score for each water company

EE for each water utility at any time t is estimated based on the residuals obtained from Model (2)[24]. The value of energy inefficiency and the variances of inefficiency and noise are estimated based on the method of moments[27,28] and imposing half normal distribution for inefficiency and standard normal for noise[29]:

$$EN\left(u_i|\varepsilon_i\right) = \mu_* + \sigma_*\left[\frac{\phi(-\mu_*/\sigma_*)}{1-\Phi(-\mu_*/\sigma_*)}\right] \quad (3)$$

where ϕ is the standard normal density function and Φ denotes the standard normal cumulative distribution function:

$$\mu_* = -\varepsilon_i\sigma_u^2/\left(\sigma_u^2+\sigma_v^2\right) \tag{4}$$

$$\sigma_*^2 = \sigma_u^2\sigma_v^2/\left(\sigma_u^2+\sigma_v^2\right) \tag{5}$$

Based on energy inefficiency estimated, $\hat{u}_i$, the EE for any water company i at any time t is derived as follows:

$$EE_{i,t} = \exp(-\hat{u}_{i,t}) \tag{6}$$

$EE_{i,t}$ ranges from zero to one. A score of one indicates that the water company is fully energy efficient, while scores below one denote energy inefficiency, highlighting the potential to reduce energy use compared to their peers without diminishing the generation of outputs.

Stage 3. Quantification of potential energy use savings

For energy inefficient water companies, potential energy use savings are estimated as follows:

$$PEN_{i,t} = EN_{i,t} \times \left(1-EE_{i,t}\right) \tag{7}$$

where $EN_{i,t}$ is the actual energy consumption for each water utility i at any time t, expressed in kWh/year, and $EE_{i,t}$ is the EE score estimated on Eq. (6).

Energy productivity estimation

EP estimation involves extending EE to a temporal setting by evaluating how water companies' energy performance has evolved over time. The methodological approach applied consists of three stages, defined as follows:

Stage 1: Definition of the energy distance function:

The energy distance function is an input distance function, as energy is an input required to deliver water. According to Färe et al.[30] an input distance function indicates the maximum reduction of inputs for a given level of outputs. Hence, the energy distance function shown in Eq. (8) measures the maximum reduction in energy use needed to produce specific outputs by water companies:

$$D_t\left(x_t, y_t\right) = \max\left\{\xi : \left(\frac{x_t}{\xi}\right) \in L_t\left(y_t\right), \xi>0\right\} \tag{8}$$

where ξ shows the maximum contraction of inputs (energy), $1/\xi$, for a given level of outputs and $L(y)$ represents the input set, i.e., the vector of inputs employed to produce the vector of outputs[31].

Stage 2. Definition of the energy productivity index (EPI) and its components

The estimation of the energy distance function (Eq. 8) for two periods, t and $t+1$, allows defining an EPI, which provides information about changes in energetic performance over the periods considered:

$$EPI_{t,t+1} = \left(\frac{D_t\left(x_t, y_t\right)}{D_t\left(x_{t+1}, y_{t+1}\right)} \times \frac{D_{t+1}\left(x_t, y_t\right)}{D_{t+1}\left(x_{t+1}, y_{t+1}\right)}\right)^{1/2} \tag{9}$$

The EPI is decomposed into two components: EEC (Eq. 10) and ETC (Eq. 11):

$$EEC_{t,t+1} = \left(\frac{D_{t+1}\left(x_{t+1}, y_{t+1}\right)}{D_t\left(x_t, y_t\right)}\right) \tag{10}$$

$$ETC_{t,t+1} = \left(\frac{D_t\left(x_{t+1}, y_{t+1}\right)}{D_{t+1}\left(x_{t+1}, y_{t+1}\right)} \times \frac{D_t\left(x_t, y_t\right)}{D_{t+1}\left(x_t, y_t\right)}\right)^{1/2} \tag{11}$$

EEC is known as "catch-up" as it measures the extent to which each water company has approached or moved away from the energy efficient frontier, that is, the one that determines the best performance[32]. On the other hand, ETC captures the existence of technical progress or regress, indicating the positive or negative shift of the energy efficient frontier[33].

The interpretation of the $EPI_{t,t+1}$ and its components ($EEC_{t,t+1}$ and $ETC_{t,t+1}$) is analogous. A value greater than one indicates gains in energetic performance over the years (EPI), improvements in energy efficiency (EEC), and technical progress (ETC). Conversely, values lower than one for EPI, EEC and ETC indicate a decline in the overall energetic performance, a decrease in the energy efficiency, and technical regression, respectively.

Stage 3. Estimation of the EPI, EEC and ETC

The EPI and its components (EEC and ETC) defined in Eqs. (9–11) are estimated employing the StoNED method considering as well Eqs. (1–6)[27,34–36]:

$$EPI_{t,t+1} = \exp(Trend + \varepsilon(i, t+1) - \varepsilon(i, t)) \tag{13}$$

where exp (Trend) and $\exp(\varepsilon(i, t+1) - \varepsilon(i, t))$ represent ETC and EEC, respectively. ETC is estimated though the computation of the coefficients in Model (2), whereas EEC estimation involves solving Eqs. (2–6).

Case study description

The case study focuses on the English and Welsh water industry, which was privatized in 1989 by transferring the water supply and sewerage assets, along with the relevant staff, of the ten existing regional water authorities into limited companies[37]. This privatization led to the establishment of two types of water companies: WaSCs and WoCs. As in most countries, English and Welsh water companies operate as monopolies; hence, regulation plays a crucial role in protecting consumers and the environment[38]. Specifically, water companies in England and Wales are regulated by three main bodies: the Water Services Regulation Authority (Ofwat), which is the economic regulator; the Department for Environment, Food and Rural Affairs (Defra), which is the environmental regulator; and the Drinking Water Inspectorate, which is the water quality regulator[39]. Three relevant functions of Ofwat are to set water tariffs for each water company every five years according to a revenue cap model, to promote economy and efficiency, and to contribute to the achievement of sustainable development[37].

WaSCs provide both water and sanitation services, whereas WoCs provide only water services. Therefore, to compare the energetic performance of both types of water companies, the case study focuses on assessing the EE and EP in the provision of water services by both types of companies. Based on available statistical data, the evaluation period spans from 2008 to 2020, encompassing three regulatory periods. The total number of observations assessed was 228.

The selection of variables for assessing the energetic performance of water companies was based on data availability and results from previous studies[40–43]. The energy used for abstracting raw water from water bodies, treating it to produce drinking water, and distributing it to consumers was selected as the input. Since the study focused on drinking water services, two outputs related to the main function of water companies were considered: (i) the volume of drinking water delivered and (ii) the number of water connections. Both outputs are relevant as they are directly related to the scale at which each water company operates[44]. For consistency, energy used and water delivered were expressed in MWh per year and Ml per year, respectively.

Environmental variables potentially impacting the energy performance of water companies were selected using the same criteria as for selecting inputs and outputs. The main source of raw water was included in the assessment by integrating the percentage of surface water and groundwater abstracted to produce drinking water. The quality of raw water was also identified as a determinant of energy efficiency in drinking water treatment plants[45]. Consequently, the number of works required at treatment plants to clean water from surface and groundwater sources and the percentage of raw water necessitating high levels of treatment were incorporated into the assessment[46]. Finally, population density, defined as the

Table 3 | Average and total values of the input and outputs for energy performance assessment of water companies in England and Wales

Year	Average values			Total values		
	Energy consumed (MWh /year)	Water connected properties (10^3)	Volume of water delivered (Ml/year)	Energy consumed (MWh /year)	Water connected properties (10^3)	Volume of water delivered (Ml/year)
2008	196,421	1369	707	3,339,158	23,271	12,020
2009	195,216	1350	681	3,513,889	24,309	12,265
2010	193,734	1356	682	3,487,214	24,405	12,280
2011	193,135	1361	685	3,476,433	24,496	12,333
2012	198,779	1368	681	3,578,019	24,624	12,259
2013	189,288	1390	660	3,407,190	25,026	11,889
2014	191,338	1398	672	3,444,089	25,162	12,097
2015	190,877	1411	669	3,435,794	25,392	12,038
2016	193,885	1421	673	3,489,929	25,586	12,118
2017	208,795	1515	719	3,549,519	25,750	12,231
2018	212,705	1528	726	3,615,983	25,980	12,339
2019	223,062	1638	749	3,668,987	26,215	11,978
2020	224,027	1652	745	3,736,436	26,428	11,926

Table 4 | Average values of environmental variables considered for energy performance assessment of water companies in England and Wales

Year	Percentage of surface water	Percentage of groundwater	Number of surface water treatment works	Number of groundwater treatment works	Percentage of water receiving high levels of treatment	Population density (10^3/Km)
2008	0.349	0.378	16	48	0.581	0.461
2009	0.296	0.403	15	49	0.596	0.458
2010	0.312	0.406	15	49	0.594	0.461
2011	0.314	0.408	15	49	0.595	0.464
2012	0.319	0.403	15	50	0.598	0.466
2013	0.332	0.404	15	49	0.589	0.453
2014	0.294	0.386	15	49	0.599	0.459
2015	0.288	0.395	16	49	0.598	0.466
2016	0.304	0.390	16	48	0.604	0.469
2017	0.244	0.395	16	50	0.590	0.474
2018	0.218	0.312	15	48	0.567	0.480
2019	0.230	0.420	16	51	0.548	0.498
2020	0.231	0.420	16	51	0.548	0.503

number of people served divided by the length of water mains, was included in the assessment to account for potential economies of density in the energetic performance of water companies[47].

Tables 3 and 4 present the main statistical values of the inputs and outputs (Table 3) and environmental variables (Table 4) involved in the energetic performance of water companies in England and Wales.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability

The codes generated and/or used during the current study are available from the corresponding author upon reasonable request.

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Author contributions

Ramón Sala-Garrido: Data curation; Writing – Review & Editing. Manuel Mocholi-Arce: Software; Writing – Review & Editing. Alexandros Maziotis: Methodology; Software; Writing – Original Draft. María Molinos-Senante: Conceptualization; Visualization; Writing – Review & Editing.

Competing interests

The authors declare no competing interests.

Additional information

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