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The evolution of benchmaking the carbon efficiency drinking water companies in England and Wales

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ABSTRACT

Water utilities face the challenge of transitioning to a low-carbon urban water cycle while reducing operational costs. This study evaluates the static and dynamic carbon efficiency of a sample of water companies from 2013 to 2018 operating in England and Wales. Each company was evaluated relative to itself and its peers using cross-efficiency Data Envelopment Analysis techniques. The results showed that the carbon performance of the water industry improved by 2.1% per year, mainly due to efficiency change. In contrast, the contribution of factors driving technical and scale change was almost negligible.

1. Introduction

Climate change presents several challenges to water utilities, including increased frequency and duration of droughts, floods, degraded water quality and changes in the demand for services (EPA, 2013; Wang et al., 2024). Water utilities not only need to adopt measures for adapting to climate change, but they also can implement mitigation strategies that contribute to global decarbonization. (IWA, 2022). As such, water regulators in some countries are already promoting the transition to a low-carbon urban water cycle (Molinos-Senante and Maziotis, 2021). For example, in 2019, water companies in England pledged to reach net zero on operational carbon emissions by 2030. Since then, the water industry in Scotland and Wales has committed to achieving greenhouse gas (GHG) neutrality across all emissions by 2040 (Water UK, 2022).

Researchers and policymakers regard the water-energy-GHG nexus as being at the forefront of achieving a sustainable and carbon-free water industry. Consequently, this topic has generated growing interest in the published literature, providing interesting guidelines for policymaking. Thus, Wakeel et al. (2018) highlighted that energy-intensive activities in the urban water cycle could cause GHG emissions to rise due to climate change adaptation strategies. In comparison, Chen et al. (2018) and Liao et al. (2020) stated that the positive relationship between energy use and GHG in the water cycle would be driven by future population growth and climate change. Moreover, it is widely recognised that low-carbon and low-energy solutions in the water sector should be economically viable (Ortiz et al., 2021). For instance, Lam and van der Hoek (2020) assessed the cost-effectiveness of several opportunities (e.g., renewable energy generation, household water-related management) in reducing GHG across the water and wastewater supply chain using city-level data (i.e., Amsterdam). Other studies in the USA and Australia demonstrated the long-term benefits of reducing GHG from energy efficiency savings by reducing residential water heating (Chini et al., 2016; Fane et al., 2020). As a result, governments have urged all sectors (including water) to substantially reduce carbon emissions by 2050 (Parliament of the UK, 2008; Ananda, 2018; Ballard et al., 2018; Lam and van der Hoek, 2020). Therefore, by quantifying energy costs and GHG performance, water utilities could establish how to provide water to their customers in an economical and environmentally sustainable way (Ananda, 2019).

Efficiency frameworks are required to assess water utilities' economic and environmental performance (eco-performance) (D'Inverno et al., 2021). Such frameworks measure the ability of given water utilities to minimise the use of inputs (costs) and undesirable outputs (such as GHG) for a given level of output (volume of drinking water supplied). Previously, Goh and See (2021) identified two main techniques that can be used to assess the performance of a water utility relative to its best industry frontier. These techniques were (1) parametric (econometric, e.g. Stochastic Frontier Analysis [SFA]) and (2) non-parametric (linear programming, e.g. Data Envelopment Analysis [DEA]). While both

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approaches have advantages and disadvantages, DEA stands out in the framework of water utilities because it does not require a functional form a priori to estimate the unknown production technology (Suárez-Varela et al., 2017). Thus, our study focused on using DEA (non-parametric) techniques to measure the eco-performance of water utilities.

Ananda and Hampf (2015) and Ananda (2018, 2019) measured the performance of several water utilities in Australia using GHG as an undesirable output. In comparison, Molinos-Senante and Maziotis (2021) focused on analysing the impact of GHG emissions on productivity changes for English and Welsh water companies. The authors concluded that including GHG emissions in productivity analysis impacted the results. However, the main limitation of these studies is that they estimated the carbon performance of water utilities using traditional DEA techniques. Consequently, the evaluation was based on a self-evaluation framework that potentially overestimated efficiency scores (Ding et al., 2019). To overcome this limitation, Doyle and Green (1994, 1995) introduced cross-efficiency DEA techniques, whereby each Decision Making Unit (DMU) (i.e. water companies) is evaluated relative to itself and its peers. Moreover, to ensure that the weightings of this technique are optimal, Sexton et al. (1986) and Doyle and Green (1994, 1995) introduced several secondary optimisation methods. Examples include aggressive and benevolent cross-efficiency DEA, in which units are considered competitors and collaborators, respectively (Liu et al., 2017; Lee et al., 2021; Jomthanachai et al., 2021). Wang and Chin (2010) and Ding et al. (2019) developed a neutral cross-efficiency DEA model, assuming that the efficiency of each unit is determined using weightings from its perspective only, without considering any effects on other DMUs.

Because of the positive features of cross-efficiency DEA techniques, these techniques have been widely used to assess the efficiency of several sectors globally (Aldamak and Zolfaghari, 2017; Aparicio et al., 2020), including energy (Ding et al., 2019), airlines (Cui and Li, 2020), agriculture (Bevilacqua et al., 2015). However, to our knowledge, this methodological approach has not been used to evaluate dynamic[1] carbon efficiency (DCE) in the water industry.

Thus, this study aimed to evaluate the static and dynamic carbon efficiency of a sample of English and Welsh water companies from 2013 to 2018, avoiding the overestimation of efficiency scores and allocating optimal weights to each variable. The first objective was to estimate static carbon efficiency (SCE) scores for a sample of water utilities. The second objective was to extend the static carbon efficiency assessment to an inter-temporal setting, whereby we evaluated the DCE of water utilities, breaking down this composite index into carbon-related efficiency change (CEC), carbon-related technical change (CTC) and carbon-related scale efficiency change (CSEC). The third objective was to identify the impacts of environmental variables on companies' DCE. The empirical component of our study focused on the water services provided by several water companies in England and Wales from 2013 to 2018. Our results are expected to provide baseline information to improve policy decisions in this sector to achieve the targets defined in several Sustainable Goals such as SDG6 (clean water and sanitation), SDG7 (affordable and clean energy) and SDG13 (climate action) (UN, 2015).

Our study has the following contributions to existing knowledge. This study pioneers the cross-efficiency DEA techniques to estimate carbon efficiency and its changes over time. This methodological approach ensures that the weights assigned to each variable in the assessment are optimized, providing more accurate and reliable results. This study is the first to decompose DCE into three components: CEC, CTC, and CSEC. This decomposition allows for a deeper understanding of the key drivers influencing changes in carbon efficiency. Insights from this analysis can inform the development and implementation of measures to enhance water companies' carbon emissions performance, thereby supporting broader environmental sustainability goals.

2. Methodology

2.1. Estimation of static carbon efficiency scores

The methodology used to estimate the SCE and DCE scores of several water companies in England and Wales is based on cross-efficiency DEA techniques. Let us assume that we have m Decision Making Units ($DMUs_j$) (i.e. water companies) that produce a set of desirable outputs, y_{kj} where $k = 1,..,l$, and a set of undesirable outputs, b_{rj}, where $r = 1,..,s$ using a set of inputs, x_{ij}, where $i = 1,..,n$. The SCE of each water company relative to itself, θ_{dd}, is derived by solving the following linear programming:

$$Max\ \theta_{dd} = \sum_{k=1}^{l} u_{kd} y_{kd} + \sum_{r=1}^{s} w_{rd} b_{rd} \tag{1}$$

$$\sum_{i=1}^{n} v_{id} x_{id} = 1$$

$$\sum_{i=1}^{n} v_{id} x_{ij} - \sum_{k=1}^{l} u_{kd} y_{kj} - \sum_{r=1}^{s} w_{rd} b_{rj} \geq 0 \quad j = 1, \ldots, m$$

$$v_{id} \geq 0, u_{kd} \geq 0, w_{rd} \geq 0$$

where $u_{kd}, w_{rd}, and\ v_{id}$ are the weights for each desirable output, undesirable output, and input, respectively. Model (1) is the traditional DEA model, in which the efficiency of each water company is derived using its most favourable weightings (self-evaluation) (Aparicio and Zofío, 2020). Thus, inputs and outputs that are favourable to a particular water company have a higher weighting, whereas those that are not favourable to a particular water company have a lower weighting or are even disregarded (Wang and Chin, 2010). The weights allocated to the variables used to estimate performance scores might be unrealistic, and efficiency scores might be overestimated.

To overcome this limitation, Sexton et al. (1986) developed the cross-efficiency DEA technique, in which the efficiency of each water company is evaluated relative to itself and its peers. However, the weightings derived from the cross-efficiency DEA techniques might not be unique (Moeini et al., 2015). To overcome this issue, Doyle and Green (1994, 1995) proposed using secondary goals to optimize weightings, in which water companies could be considered competitors or collaborators and aggressive or benevolent, respectively. Subsequently, Wang and Chin (2010) and Ding et al. (2019) adopted the neutral approach, whereby the efficiency of each water company is determined using weightings only from its perspective, without considering the effects on other DMUs. The following linear programming model is solved To estimate SCE scores based on the neutral DEA approach:

$$Max\ \beta \tag{2}$$

$$\sum_{i=1}^{n} v_{id} x_{id} = 1$$

$$\sum_{i=1}^{n} v_{id} x_{ij} - \sum_{k=1}^{l} u_{kd} y_{kj} - \sum_{r=1}^{s} w_{rd} b_{rj} \geq 0 \quad j = 1, \ldots, m, j \neq d$$

[1] Of note, efficiency is a static assessment that does not account for changes to the performance of water companies over time. Yet, assessing changes to performance involves extending the notion of efficiency to an inter-temporal setting (Mahlberg et al., 2011). Moreover, dynamic efficiency allows the efficiency over a given time period to be computed, and the performance among water companies to be compared quantitatively (Gémar et al., 2018).

$$\sum_{k=1}^{l} u_{kd}y_{kd} + \sum_{r=1}^{s} w_{rd}b_{rd} - \theta_{dd}\sum_{i=1}^{n} v_{id}x_{id} = 0$$

$$u_{kd}y_{kd} - \beta \geq 0 \quad k = 1, 2, \ldots. l$$

$$w_{rd}b_{rj} - \beta \geq 0 \quad r = 1, 2, \ldots. s$$

$$v_{id} \geq 0, u_{kd} \geq 0, w_{rd} \geq 0, \beta \geq 0$$

In Model (2), the efficiency of each DMU is subject to both self and peer evaluation. This model also reduces the likelihood of zero weightings for desirable and undesirable outputs, excluding them from the assessment exercise. After taking the optimal weightings, $u^*_{kd}, w^*_{rd}, v^*_{id}$ from Model (2), the static carbon efficiency of the water company d (SCE_{dj}) is calculated as follows:

$$SCE_{dj} = \frac{\sum_{k}^{l} u^*_{kd}y_{kj} + \sum_{r=1}^{s} w_{rd}b_{rd}}{\sum_{i=1}^{n} v_{id}x_{id}} \tag{3}$$

Consequently, the SCE of each water company j (SCE_j) is calculated as follows:

$$SCE_j = \frac{1}{m}\sum_{d=1}^{m} SCE_{dj} \tag{4}$$

2.2. Estimation of dynamic carbon efficiency scores

The SCE scores determined from Eq. (4) estimate DCE scores based on the traditional Malmquist Productivity Index (MPI). Thus, the DCE between period t and $t+1$ is defined as follows (Ding et al., 2019):

$$DCE_{t,t+1} = \left(\frac{CE^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{CE^{t+1}(x^t, y^t, b^t)} \times \frac{CE^{t}(x^{t+1}, y^{t+1}, b^{t+1})}{CE^{t}(x^t, y^t, b^t)}\right)^{\frac{1}{2}} \tag{5}$$

The DCE in Eq. (5) measures how productive water companies have been over time in terms of carbon emissions. A $DCE_{t,t+1}$ value greater than 1 implies an improvement in carbon productivity, whereas a $DCE_{t,t+1}$ value below 1 implies a deterioration in carbon productivity. Dynamic carbon efficiency can be further separated into CEC, CTC and CSEC. The decomposition of dynamic carbon efficiency is as follows:

$$\begin{aligned} DCE = {} & \frac{CE^{t+1}_{VRS}(x^{t+1}, y^{t+1}, b^{t+1})}{CE^{t}_{VRS}(x^t, y^t, b^t)} \times \frac{\frac{CE^{t+1}_{CRS}(x^{t+1}, y^{t+1}, b^{t+1})}{CE^{t+1}_{VRS}(x^{t+1}, y^{t+1}, b^{t+1})}}{\frac{CE^{t}_{CRS}(x^t, y^t, b^t)}{CE^{t}_{VRS}(x^t, y^t, b^t)}} \\ & \times \left(\frac{CE^{t}_{CRS}(x^{t+1}, y^{t+1}, b^{t+1})}{CE^{t+1}_{CRS}(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{CE^{t}_{CRS}(x^t, y^t, b^t)}{CE^{t+1}_{CRS}(x^t, y^t, b^t)}\right)^{\frac{1}{2}} = CEC \\ & \times CSEC \times CTC \end{aligned} \tag{6}$$

CEC indicates whether the daily operation of water companies has improved or deteriorated and the extent to which carbon emissions and inefficiency have changed between the two periods. A value greater than one for CEC indicates improvements in carbon efficiency change, whereas the opposite applies when CEC is below one. Technical change captures the impact of technical progress or regression. If $CTC > 1$, water companies have adopted new technologies to reduce carbon emissions, increasing productivity. A CTC value below one indicates technical regression. Increases in the scale of operations of water companies, $CSEC > 1$, could lead to higher productivity, as larger water companies might have found cheaper ways to treat and distribute water (most productive scale size), reducing carbon emissions and inefficiency.

The decomposition of DCE requires two single-period measurements to be computed under constant returns to scale (CRS), variable returns to scale (VRS), and two mixed-period technologies under CRS. Single-period efficiency scores are solved using models (1) and (2). The following additional constraint is imposed when the model is solved under variable returns to scale: $\sum_{i=1}^{n} v_{id} + \sum_{k=1}^{l} u_{kd} + \sum_{r=1}^{s} w_{rd} = 1$. The Appendix provides the linear programming models solved using mixed-period technologies under CRS. Of note, mixed-period cross-efficiency scores are also calculated using Eqs. (3) and (4).

2.3. Determinants of dynamic carbon efficiency

To improve our understanding of the determinants of DCE (i.e. changes to the carbon performance of water companies over time), we regressed the DCE scores against a set of environmental variables that could impact the carbon efficiency of water companies (Ananda, 2019; Sala-Garrido et al., 2021). These variables are related to population density, sources of raw water and type of water treatment (see Section 3 for details). As such, the following econometric model is defined and solved (Zeng et al., 2016):

$$DCE_{mt} = a_o + \gamma_i + \delta' z_{mt} + \varepsilon_{mt} \tag{7}$$

where the dependent variable DCE_{mt} captures the DCE for any water company m over time, a_o presents the constant term, γ_i captures firm-specific time-invariant unobserved heterogeneity (e.g. managerial inability), and ε_{mt} is the noise that is distributed normally. Individual effects could be fixed or random and correlated or uncorrelated with the explanatory variables, z_{mt} (Greene, 2005). If the effects are assumed to be fixed, Eq. (7) becomes the fixed effects (FE) model. If random, Eq. (7) becomes the random effects (RE) model (Wooldridge, 2010). Unobserved fixed effects are removed from the FE model by accounting for variation within water companies over time (Cameron and Trivedi, 2015) or within variation (Kumbhakar et al., 2015). The RE model is estimated using generalised least squares, which are widely used for traditional RE panel-data models (Kumbhakar et al., 2015). We used the Hausman test to determine which model to use for the analysis (Baltagi, 2005; Stock and Watson, 2020). The final model is estimated using robust standard errors to control for heteroscedasticity (Kumbhakar et al., 2015; Greene, 2018).

3. Data and sample selection

The empirical application conducted here focused on water services provided by ten English and Welsh water and sewerage companies (WaSCs) and six water-only companies (WoCs) during 2013–2018. Thus, the total number of observations is 96 (6 years * 16 water companies). The 16 water companies evaluated provide drinking water services to more than 90% of customers in England and Wales. WaSCs and WoCs are private and regulated from technical, economic and environmental dimensions by four independent bodies: the Drinking Water Inspectorate (DWI), the Environment Agency, Natural Resources Wales and the Water Services Regulation Authority (Ofwat). The DWI is the independent regulator of drinking water in England and Wales, responsible for ensuring that companies provide safe drinking water that is acceptable to consumers and meets the standards set in law. The Environment Agency protects and improves the environment and promotes sustainable development. In Wales, since April 2013, these functions have been performed by Natural Resources Wales. Ofwat is the economic regulator for the water and sewerage sectors in England and Wales. It is responsible for regulating the water industry and ensuring that water companies provide consumers with a good quality service and value for money. Every five years, Ofwat approves the final allowed revenue (price reviews) that companies can recover from customers by challenging the business plans of companies (Defra, 2014).

Inputs, desirable and undesirable outputs were selected based on previous literature reviews and data availability (see, for instance, See, 2015; Pinto et al., 2017; Goh and See, 2021). Two inputs are used to estimate static and dynamic carbon efficiency scores. The first input is the annual energy expenditure of water services measured in millions of pounds sterling (£) (Sala-Garrido et al., 2021; Walker et al., 2020). The second input is defined as other expenditures related to water services. This input is calculated as the difference between total operating and energy expenditures. Other expenditures (costs) are measured in millions of £ per year (Mellah and Ben Amor, 2016; Molinos-Senante and Maziotis, 2018).

We use two desirable outputs. The first desirable output is the volume of drinking water delivered per year. This output is measured in thousands of cubic metres per year (Ananda and Hampf, 2015; Ananda, 2018; D'Inverno et al., 2021). The second desirable output is the number of water-connected properties measured in thousands of customers. The undesirable output is defined as greenhouse gas emissions from the provision of water services. It is expressed as CO_{2eq}, the annual equivalent of tonnes of CO_2 (Ofwat, 2010a, 2010b; Molinos-Senante and Maziotis, 2022). The water companies monitor and estimate GHG emissions according to the United Kingdom Government Environmental Reporting Guidelines (HM Government, 2019). English and Welsh water companies report direct and indirect GHG emissions associated with the direct operation of the water companies, purchase and use of electricity and other indirect activities (Ofwat, 2010a).

Several environmental variables are selected to evaluate the factors changing carbon efficiency over time. The relationship of these factors with previously estimated DCE scores is analysed. These variables are based on the source of water, population density and treatment complexity of water services (Ofwat, 2019; Villegas et al., 2019; Walker et al., 2019). The following variables are used in the regression analysis: 1) the percentage of water taken from boreholes, 2) the percentage of water taken from reservoirs, and 3) the average pumping head. These variables are used to capture the source of raw water. For instance, higher energy requirements (average pumping head) to pump water to the network might lead to higher carbon emissions and, thus, lower inefficiency and productivity. We also include the following variables to capture the input requirements when treating water: 1) the number of treatment works from surface water resources (CEPA, 2018), 2) the number of treatment works from groundwater resources, and 3) the percentage of raw water for which treatment needs between 3 and 8 operational units to produce drinking water (Ofwat, 2018, 2019; Walker et al., 2019). Population density is measured by the ratio of water population to water area, measured as thousands per km^2 (Walker et al., 2020). Table 1 presents the descriptive statistics of the variables used to estimate static and dynamic carbon efficiency scores.

4. Results

4.1. Static carbon efficiency scores

SEC scores for English and Welsh WaSCs and WoCs during 2013–2018 are shown in Fig. 1. The average SCE for all evaluated water companies was 0.74 (assuming CRS and VRS technologies were used). On average, English and Welsh water companies could save around 26% of GHG emissions during these six years. Except for 2018, the SCE of water companies generally improved over time. Thus, both water companies and the regulator are highly relevant in reducing the carbon footprint of the urban water cycle.

Regardless of the assumption made on technology used based on company size (i.e. CRS or VRS), WoCs were slightly more carbon efficient than WaSCs (Fig. 1). Under VRS, average WoCs reported a carbon efficiency score of 0.752 and would need to cut carbon emissions by a further 24.8% to become more environmentally efficient. In contrast, average WaSCs must reduce carbon emissions by 26.1% to provide the same service levels as WoCs. At the beginning of the period, WaCs reported higher carbon efficiency levels than WoCs. However, over time, WoCs managed to catch up with WaSCs to become more carbon-efficient. Higher costs and higher carbon emissions levels drove the decline in the average carbon efficiency of WaSCs between 2016 and 2018. Compared to 2013, the average WoC improved its carbon efficiency by 18.14%.

In contrast, the SCE of the average WaSC slightly declined by 0.29%. However, in 2018, SCE declined for both WaSCs and WoCs due to higher energy and other costs. This decline offsets any gains from reducing GHG emissions, leading to lower levels of carbon efficiency. Although WoCs were more carbon efficient than WaSCs, the results demonstrated that carbon inefficiency exists in the English and Welsh water industry and can potentially reduce GHG emissions.

4.2. Dynamic carbon efficiency scores and its drivers

The average DCE for all companies was 1.021, with the performance of English and Welsh water companies improving by 2.1% per year (Fig. 2). This improvement was greater in WaSCs (2.4% improvement annually) than in WoCs (0.5% improvement annually). The cumulative value for DCE (total change in carbon performance) was better for WaSCs than WoCs over the study period. During these six years, the carbon performance of English and Welsh WaSCs and WoCs improved by 12.0% and 2.4%, respectively. Overall, the water industry in England and Wales experienced a 10.0% improvement in carbon performance. Except for 2013, the DCE scores of WaSCs were higher than 1.0 for all other years. In contrast, the DCE scores of WoCs declined in three out of the six years analysed. Thus, WaSCs have put more effort into improving GHG emission performance than WoCs.

On average, all components (i.e. CEC, CTC and CSEC) positively contributed to changes in DCE scores (carbon productivity). The improvement in DCE was attributed to an increase in efficiency by 2.1% per year, a scale efficiency change of 0.13% per year, and a technical change of 0.27% per year. Except for 2013–2014, in all other years, water companies were productive in reducing carbon emissions (Fig. 3).

Table 1
Descriptive variables used to estimate static and dynamic carbon efficiency scores of English and Welsh water companies.

Type of variable	Variables	Unit of measurement	Mean	Std. Dev.	Minimum	Maximum
Desirable outputs	Volume of water delivered	000 s m^3/year	260193	202476	20502	791616
	Number of water-connected properties	000 s/year	1499	1125	124	3826
Undesirable output	Greenhouse gas emissions	tonCO_{2eq}/year	82845	69062	4542	275900
Inputs	Energy expenditure	£m/year	20.4	15.0	1.7	60.0
	Other expenditure	£m/year	93.4	78.9	7.6	331.6
Environmental variables	Water taken from reservoirs	%	37.0	26.2	0.0	95.7
	Water taken from boreholes	%	40.1	31.2	3.0	92.4
	Surface water treatment works	nr	16.18	15.32	1.00	54.00
	Groundwater treatment works	nr	50.83	40.34	2.00	127.00
	Water receiving high levels of treatment	%	93.2	5.1	81.2	100.0
	Average pumping head	nr	147	44	65	256
	Population density	000 s/km^2	0.47	0.29	0.15	1.25

Observations: 96.
Energy and other expenditures are expressed in 2018 prices.

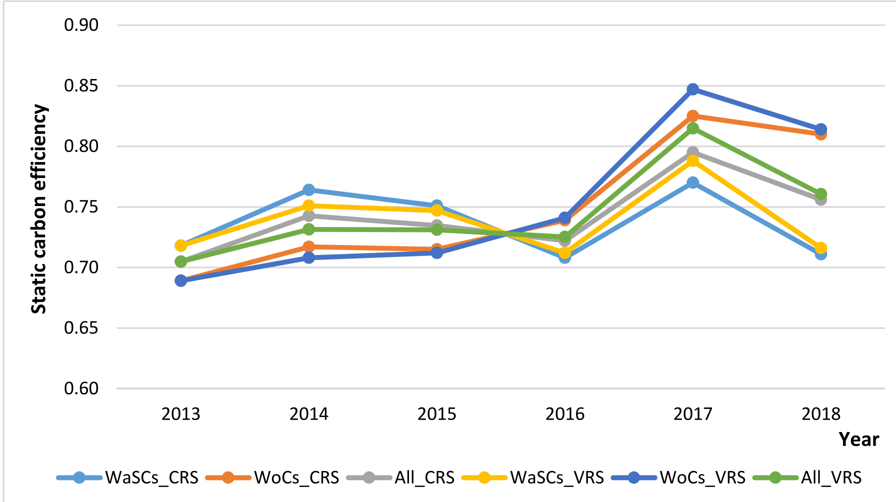

Fig. 1. Average static carbon efficiency for all English and Welsh water companies, water and sewerage companies (WaSCs) and water-only companies (WoCs) assuming constant returns to scale (CRS) and variable returns to scale (VRS).

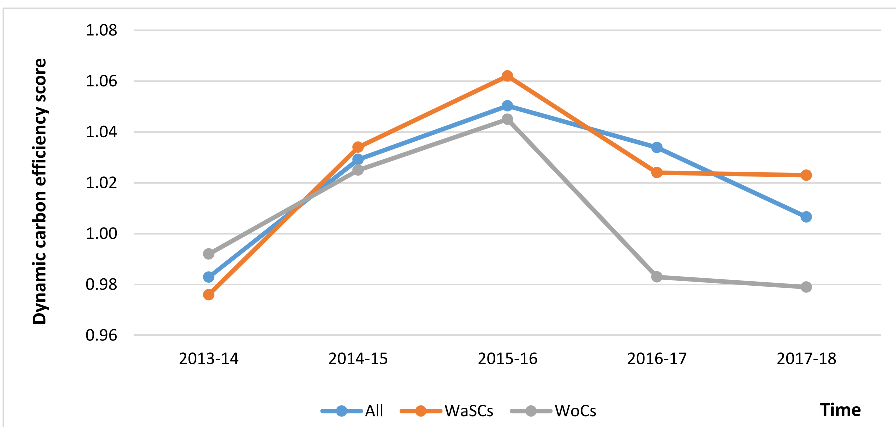

Fig. 2. Average dynamic carbon efficiency for all English and Welsh water companies, water and sewerage companies (WaSCs) and water-only companies (WoCs).

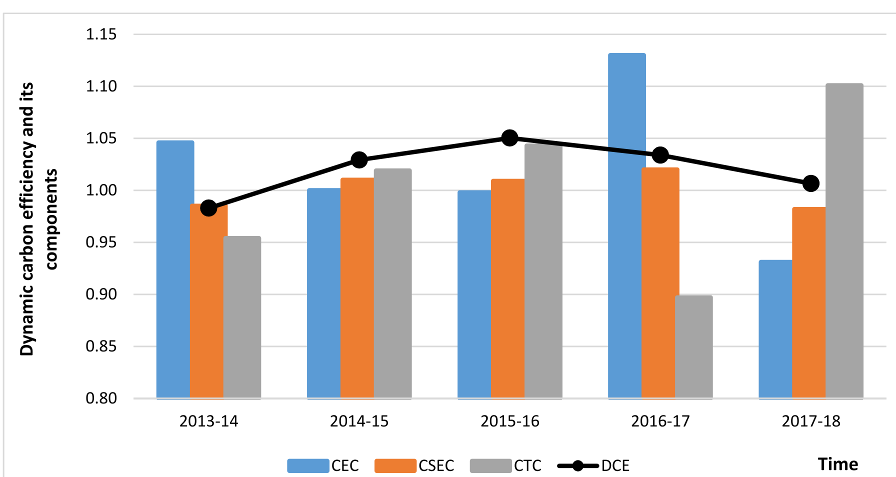

Fig. 3. Average dynamic carbon efficiency and its drivers for English and Welsh water companies.

Over the six years, the average DCE declined due to a reduction in technical change and scale efficiency change. The limited adoption of environmentally friendly technologies and increased size of companies might have hindered productivity.

In contrast, improvements in daily operations appeared to cause carbon emissions and inefficiency to decline, contributing positively to productivity. The situation changed in the following years. Both technical progress and movement toward the optimal scale positively impacted productivity, which increased by 1.9% and 1%, respectively. However, efficiency change appeared to have a limited impact on carbon productivity. During 2015–2016, carbon productivity increased by 1.7%, primarily due to adopting best management practices, which could have led to lower carbon emissions and higher productivity. However, there was a clear downward trend from 2017 to 2018. This trend was mainly attributed to considerable losses in carbon and scale efficiency changes. Thus, increases in production costs likely have a detrimental impact on the productivity of companies. The results suggest that water companies could improve productivity by investing in technologies that reduce production costs, such as using renewable energy in water treatment.

Improved DCE in WaSCs was mainly attributed to an increase in technical change of 2.2% (Figs. 4 and 5). Although efficiency change and scale efficiency change were positive, they had a limited impact on productivity. In contrast, the slight improvement in DCE by WoCs was mainly attributed to considerable gains in carbon efficiency (Figs. 4 and 5). This finding was expected because the efficiency of WoCs considerably improved over time, reporting higher efficiency scores compared to WaSCs (Fig. 1). Losses in scale efficiency change and the lack of new technologies negatively impacted the DCE of WoCs.

4.3. Environmental variables influencing dynamic carbon performance

To establish the factors driving the DCE of water companies, we examined the econometric results after obtaining FE model estimates with robust standard errors (Table 2). The Appendix shows the preliminary results of the FE and RE model estimates and the Hausman test, which justifies using the FE model. The carbon performance of water companies was significantly affected by water treatment when taken from surface and groundwater resources, high levels of water treatment, average pumping head and population density. Based on the magnitude of the coefficients, high levels of water treatment and population density had the greatest impact on the DCE of water companies. When keeping other variables constant, a unit increase in treatment and population density levels could reduce DCE by 0.166 and 0.435 units, respectively.

When the complexity of raw water treatment increases, energy costs and the level of GHG emissions released into the atmosphere also tend to rise. In parallel, with the increasing demand for water, more water must be abstracted and treated. This issue could increase input requirements and carbon emissions, leading to greater inefficiencies and lower DCE. Average pumping head values corroborate this issue. High pumping requirements to abstract and move water to treatment facilities are energy-intensive and could harm productivity if pumps are not energy-efficient.

Furthermore, more treatment works are necessary when water is taken from groundwater resources. These energy-intensive activities could release high carbon emissions and negatively influence inefficiency and productivity. In contrast, treatment works from surface water resources might not be costly, so productivity might not be negatively affected.

5. Discussion

To comprehensively analyse the linkage between DCE estimates and the regulatory cycles of the English and Welsh water industry, the period studied was divided into two distinct sub-periods corresponding to consecutive regulatory review phases: 2013–2015 and 2016–2018. During the 2013–2015 sub-period, aligned with the outcomes of the 2009 price review, regulatory frameworks introduced several financial incentive schemes to encourage water companies to enhance their financial and environmental performance simultaneously. A notable example of these regulatory innovations was the Service Incentive Mechanism (SIM). Under SIM, water companies were mandated to report their performance against a suite of performance indicators, including metrics such as water leakage rates and the frequency of unplanned service interruptions (Villegas et al., 2019). This mechanism was designed to improve service quality and increase transparency and accountability in the water sector.

In the subsequent period, 2016–2018, regulators transitioned from SIM to a more robust and comprehensive framework involving Common Performance Indicators (CPIs) and Outcome Delivery Incentives (ODIs). This change marked a significant shift in regulatory focus from monitoring and rewarding or penalizing water companies based on their performance relative to pre-set environmental targets. These targets encompassed a broader range of environmental and operational indicators, including, but not limited to, water leakages, pollution incidents, flooding incidents, and carbon emissions.

Notably, the regulatory framework evolved to include both financial and reputational incentives. Financial rewards or penalties were directly tied to achieving or failing to meet specific targets, linking financial outcomes to environmental and operational performance. Specific targets, particularly those related to carbon emissions, were simultaneously associated with reputational rewards or penalties, underscoring the industry's growing emphasis on sustainable practices. This dual approach of using CPIs and ODIs refined the accountability mechanisms

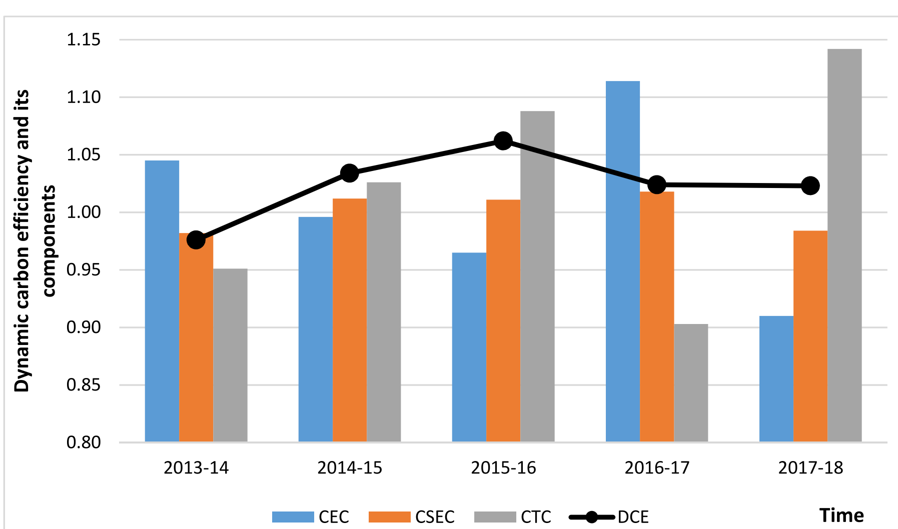

Fig. 4. Average dynamic carbon efficiency and drivers for English and Welsh water and sewerage companies (WaSCs).

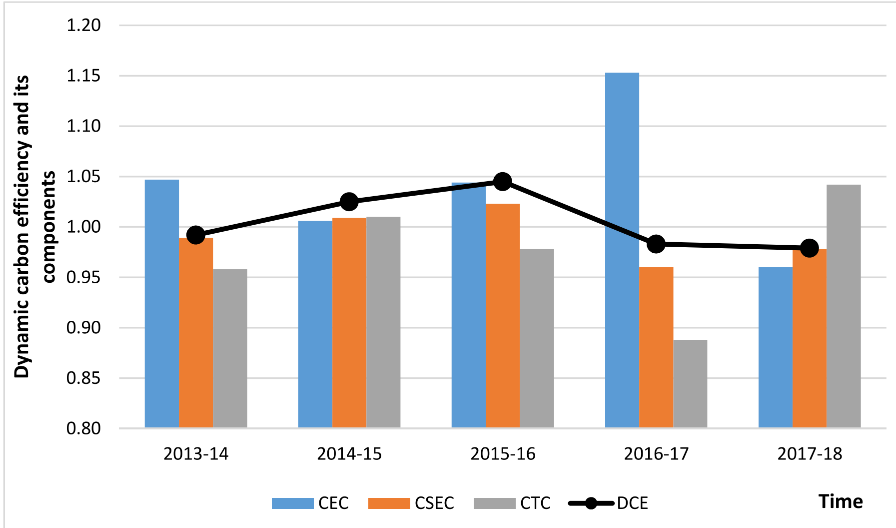

Fig. 5. Average dynamic carbon efficiency and drivers for English and Welsh water-only companies (WoCs).

Table 2
Influence of exogenous variables on dynamic carbon efficiency scores based on fixed effects model with robust standard errors.

	Coefficient	Robust Std. Err.	T-stat	p-value
Constant	1.131	0.156	**7.250**	0.000
Water taken from boreholes	−0.063	0.132	−0.480	0.641
SW treatment works	0.008	0.001	**6.230**	0.000
GW treatment works	−0.004	0.001	**−5.820**	0.000
High levels of water treatment	−0.166	0.093	***−1.780***	0.094
Average pumping head	0.000	0.000	**−2.140**	0.048
Population density	−0.327	0.035	**−9.440**	0.000
Water taken from reservoirs	0.435	0.282	1.540	0.143
F(7.16)	**29.740**			
p-value	0.000			

Number of observations: 96.

in place and aligned the interests of water companies more closely with the broader goals of sustainability and environmental stewardship. This alignment was crucial in driving improvements across the industry, as companies were compelled to innovate and optimize their operations to meet increasingly stringent standards, thereby contributing to the overall goal of sustainable urban water management.

From 2013 to 2015, DCE evaluations for WaSCs and WoCs revealed modest improvements of 0.5% and 0.9%, respectively. These enhancements were exclusively attributed to advances in carbon efficiency, suggesting that less carbon-efficient water companies made significant strides in refining their daily operations by reducing production costs and GHG emissions, thereby approaching the performance levels of more efficient peers. Specifically, gains in carbon efficiency were recorded at 2.1% for the average WaSC and 2.7% for the average WoC. Additionally, the scale efficiency change maintained a value close to unity, indicating that these companies were operating at optimal scales. Despite these advancements, it was noted that any gains in carbon efficiency were negated by technical regression, which overshadowed the positive developments in carbon management.

In the subsequent period from 2016 to 2018, the average WaSC DCE improved significantly by 3.6%, with this enhancement wholly ascribed to technical progress. This period also saw minor positive shifts in scale efficiency, suggesting that incremental increases in operational scale might have contributed to reductions in overall production costs for WaSCs. However, these gains were partially offset by losses in carbon efficiency, which adversely affected the DCE of WaSCs. Conversely, while the average DCE for WoCs remained positive, it exhibited a declining trend. Setbacks in technical change and scale adjustments counterbalanced notable gains in carbon efficiency. The improvements in management practices led to substantial gains in carbon efficiency, averaging 5.2%. Nevertheless, adjustments in company scale had a detrimental impact on DCE, decreasing it by 1.3%. The absence of new technological adoption possibly exacerbated production costs and carbon emissions.

The analysis indicates that while WaSCs can potentially enhance their DCE by continuously improving efficiency over time, WoCs stand to gain significantly in carbon productivity through adopting technological leadership. These findings highlight the critical need for both types of companies to balance operational scale, carbon efficiency, and technical advancements to optimize their overall performance and contribute effectively to sustainable urban water management.

6. Conclusions

Understanding production costs and carbon emission performance is essential for water companies to sustainably deliver services to their customers. This objective can be achieved by estimating the static and dynamic carbon efficiency scores of water companies. However, robust and reliable methods are required to apply these results to establish objective carbon reduction targets and regulatory policies. This study used a cross-efficiency evaluation framework to evaluate the static and dynamic carbon efficiency of several water companies in England and Wales.

Our study showed that static carbon inefficiency exists in the water industry. WaSCs and WoCs need to further reduce costs and carbon emissions by up to 26% to maintain the same output level. WoCs tended to be slightly more carbon efficient compared to WaSCs. At the start of the six years, WaSCs performed better than WoCs. However, this situation changed from 2016 to 2018. WoCs became more efficient at reducing costs and carbon emissions, achieving considerable gains in efficiency over time. Over time, the DCE of the water industry improved by 21.0% on average, with all components contributing positively. Average CEC increased by 10.5%, whereas CSEC and CTC improved by 0.6% and 1.4%, respectively.

Based on DCE estimates, WaSCs were more productive than WoCs. The DCE of average WaSCs improved by 2.4% per year, entirely attributed to technical progress. Thus, adopting management practices could lower production costs and carbon emissions. In contrast, the DCE of average WoCs rose by 0.5% per year, mainly attributed to efficiency gains. Better management of daily operations and networks might have reduced overall costs and inefficiencies. Both WaSCs and WoCs appeared to operate toward their most productive scale size (scale efficiency change was close to unity). However, improvements in managerial practices and technologies are required. Overall, evaluation of the relationship between environmental variables and the DCE of companies showed that higher complexity of water treatment and energy costs could reduce DCE. This finding was verified by other energy-intensive activities, such as average pumping head and treatment works when water is taken from groundwater resources.

Overall, our study results have several relevant policy implications. Carbon efficiency estimations enable the English and Welsh water regulator to set progressive carbon reduction targets aligned to achieve carbon neutrality. These targets can be specifically tailored to different types of water companies, WaSCs versus WoCs, recognizing that WoCs have demonstrated notable improvements and face distinct operational challenges and efficiencies. To further incentivize performance, regulation could include economic incentives for water companies that exceed mandated carbon performance standards. Given the observed differences in carbon performance between WaSCs and WoCs, encouraging the exchange of best practices could enhance sector-wide efficiency. Promoting management strategies that have led to cost reductions and lower carbon emissions, particularly those employed by WoCs, could benefit the entire sector. Technical progress and operational efficiencies have driven improvements, suggesting that policies should support investments in new technologies and better operational management. These policies could involve subsidies or tax incentives for adopting energy-efficient technologies or for research into innovative methods that simultaneously reduce carbon emissions and operational costs. Furthermore, the study indicates that environmental factors like water treatment complexity and energy costs significantly impact carbon efficiency. Policies could, therefore, be designed to address these specific challenges, perhaps through differentiated standards or support mechanisms that consider the unique local conditions and resource bases of different water companies.

While this study makes significant contributions to understanding the carbon performance in the provision of drinking water, it is not without limitations. Firstly, although the study examines carbon performance from the static and dynamic perspectives, it does not offer a holistic assessment of water companies' overall performance. Specifically, it does not account for changes in other crucial variables such as energy costs, other costs, water delivered, and the number of water connections. Future research could address this gap by employing non-radial DEA methods, which allow for the estimation of individual performance indicators for each variable, providing a more comprehensive view of performance. Secondly, the range of environmental variables included in the analysis was constrained by data availability. Expanding the scope to incorporate additional environmental variables could enrich the analysis, offering deeper insights into their effects on the carbon performance of water companies. Such an extension would enhance the robustness of the findings and potentially reveal new areas for policy intervention and performance improvement.

CRediT authorship contribution statement

Manuel Mocholi-Arce: Writing – review & editing, Supervision, Data curation. **Ramon Sala-Garrido:** Writing – review & editing, Methodology. **Alexandros Maziotis:** Writing – original draft, Project administration, Methodology, Conceptualization. **Maria Molinos-Senante:** Writing – review & editing, Resources, Funding acquisition, Formal analysis.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jup.2024.101836.

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