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Comparing Operational, Environmental and Eco-Efficiency of Water Companies in England and Wales

Ramón Sala-Garrido ¹ , Manuel Mocholí-Arce ¹ , María Molinos-Senante ^{2,*} and Alexandros Maziotis ²

¹ Departamento de Matemáticas para la Economía y la Empresa, Universidad de Valencia, 46071 Valencia, Spain; sala@uv.es (R.S.-G.); Manuel.mocholi@uv.es (M.M.-A.)

² Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile, Santiago 4860, Chile; alexandros.maziotis@gmail.com

* Correspondence: mmolinos@uc.cl; Tel.: +56-971934218

Abstract: The assessment of performance of water companies is essential for their regulation. In doing so, several variables and models can be employed. This study evaluates and compares the performance of a sample of English and Welsh water companies from the operational, environmental and eco-efficiency perspectives by applying the non-radial data envelopment analysis range adjusted measure model. This methodological approach allows integrating greenhouse gas emissions as undesirable output. The results indicated that the water industry performed well from an operational perspective. However, environmental inefficiency considerably exists which illustrates the difficulties of the water companies in reducing greenhouse gas emissions. The average eco-efficiency was 0.783 which means that while expanding water services, water companies could further reduce costs and carbon emissions by 11.7% on average. Other factors such as water treatment complexity and population density significantly affect water companies' eco-efficiency. Several policy implications are finally discussed.

Keywords: eco-efficiency; greenhouse gas emissions; non-radial DEA; water treatment and supply; water utilities; sustainability

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1. Introduction

Water companies are obliged to deliver drinking water according to quality standards defined by the water regulator and safely discharge treated wastewater to the environment using minimum economic costs [1]. The supply of water and wastewater services releases greenhouse gas emissions (GHG) to the atmosphere which are mainly because of energy use in all parts of the supply chain [2,3]. Over the years, researchers and policy makers have been making efforts to understand the water-energy-GHG nexus because it impacts climate change [4]. For instance, Lam et al. [5], Lee et al. [6] and Wang et al. [7] concluded that the energy requirements in water and wastewater production process could potentially increase due to population growth and climate change. Thus, the need to invest in new technologies that could reduce the carbon emissions during the water and wastewater production process is of outmost importance for sustainable development [8]. Policy makers in several countries around the world set targets in reducing GHG emissions in all sectors in economy including the water sector. For instance, the state of Victoria in Australia is committed to reduce GHG to zero by 2050 [9]. The United Kingdom Government is also committed that the water sector should cut down its GHG emissions by 80% by 2050 [10].

Traditionally the measurement of performance of water production process was conducted including inputs (e.g., operational costs) and desirable outputs (e.g., volumes of water delivered) employed by water utilities. In other words, it has been evaluated the efficiency of water utilities in the provision of drinking water [11–13]. More recently, several undesirable outputs such as water leakage were included in the analysis based on the approach developed by Chung et al. [14] and Fare and Grosskopf [15]. Recent studies

by Ananda and Kampf [4], Ananda [8,16] included in their analysis, as undesirable outputs, GHG emissions from the operation of water and sewerage facilities. This assessment allows estimating jointly the economic and environmental performance of water utilities, i.e., its eco-efficiency.

According to the literature review conducted by Goh and See [13], the eco-efficiency assessment of water utilities has been done by using production frontiers that could be estimated using parametric (econometric) and non-parametric (linear programming (LP)) techniques. The most widely used non-parametric technique is the Data Envelopment Analysis (DEA) [16,17] which compares the performance of each unit (water utility) relative to the best industry's frontier [18]. Unlike parametric techniques, DEA does not presume a priori a functional form for the technology [19] so this technique is used in this study.

There are two main groups of DEA models; the radial and non-radial models [20]. Charnes et al. [18] and Banker et al. [21] developed the radial DEA models. In these models, the technical efficiency (and also eco-efficiency) is estimated as a score in the objective function of the LP model [22]. However, these models assume a proportional contraction of all inputs while output remains fixed. Consequently, this is a relevant limitation of radial DEA models [23,24]. On the other hand, the non-radial DEA models estimated the technical efficiency using slacks [22]. This permits estimating the efficiency of each input or each output [23]. There are several examples of non-radial DEA models such as the additive model established by Charnes et al. [24], the slack-based model introduced by Tone [25], the "range-adjusted measure" (RAM) advanced by Cooper et al. [26–30], the enhanced Russel graph measure of efficiency [31]. While each non-radial DEA model has pros and cons, the RAM-DEA model can easily integrate operational and environmental efficiency for each water utility in a united manner [32–37]. Thus, the RAM-DEA model is used in our study to evaluate the eco-efficiency of water supply process. Given the positive features of the RAM-DEA model, there have been several studies that calculated the eco-efficiency of companies in the energy sector (for a review see Sueyoshi et al. [27]). However, to the best of authors' knowledge there have not been any studies in the water industry evaluating its eco-efficiency by employing the RAM-DEA approach.

Consequently, the core objective of this study is to evaluate and compare the operational efficiency (OE), environmental efficiency (EE), and eco-efficiency (ECOE) of several water utilities using RAM-DEA models. In doing so, we employed three non-radial DEA models. The first one estimates OE by expanding desirable outputs (i.e., drinking water delivered and water connected properties) and contracting inputs (i.e., operational costs). The second model estimates EE by contracting inputs and undesirable outputs (i.e., GHG emissions). The third non-radial DEA model integrates both operational and environmental efficiency in a unified framework [38,39], i.e., it estimates the ECOE of water utilities. This is a novel approach, as to the best of authors' knowledge, this is the first study that assessed the eco-efficiency of water production process using non-radial RAM-DEA techniques. As we want to get a better insight on what drives companies' efficiency, we further regress the eco-efficiency scores against a set of environmental factors. The empirical approach deals with the drinking water services provided by several water and sewerage companies (WaSCs) and water only companies (WoCs) in England and Wales during the years 2011–2018. We also relate the findings to the regulatory cycle to discuss the effect of regulation on companies' eco-efficiency. The paper concludes with the discussion of several policy implications.

2. Materials and Methods

2.1. Estimation of Operational Efficiency, Environmental Efficiency and Eco-Efficiency

This section describes the methodology employed to assess the OE, EE, and ECOE of several water utilities (companies) in England and Wales using RAM-DEA models. We suppose that k water utilities exist and the j th company ($j = 1, \dots, k$) use a vector of m inputs $X_j = (x_{j1}, \dots, x_{jm})$ to generate a set of s desirable outputs $Y_j = (y_{j1}, \dots, y_{js})$ and

r undesirable outputs $B_j = (b_{j1}, \dots, b_{jr})$. The OE of the particular n th water company can be evaluated using the following RAM-DEA model:

$$\begin{aligned} & \max \frac{\left(\sum_{i=1}^m \frac{d_i^x}{R_i^x} + \sum_{q=1}^s \frac{d_q^y}{R_q^y} \right)}{(m+r)} \\ & \text{s.t.} \\ & \sum_{i=1}^k x_{ij} \lambda_{ij} + d_i^x = x_{in} \quad (i = 1, \dots, m) \\ & \sum_{j=1}^k y_{qj} - d_q^y = y_{qn} \quad (q = 1, \dots, s) \\ & \sum_{j=1}^k \lambda_j = 1, \quad \lambda_j \geq 0 \quad (j = 1, \dots, k) \\ & d_i^x \geq 0 \quad (i = 1, \dots, m) \\ & d_q^y \geq 0 \quad (q = 1, \dots, s) \end{aligned} \quad (1)$$

where λ denotes intensity variables employed to create the production frontier, d_i^x and d_q^y are slack variables for inputs and desirable outputs, respectively. The ranges of inputs and desirable outputs are given by their upper and lower bounds as follows [36]:

$$\begin{aligned} \bar{x}_i &= \max\{x_{ij}\} \text{ and } \bar{y}_q = \max\{y_{qj}\} : \text{upper bounds} \\ \underline{x}_i &= \min\{x_{ij}\} \text{ and } \underline{y}_q = \min\{y_{qj}\} : \text{lower bounds} \end{aligned} \quad (2)$$

Then the ranges, R_i^x and R_q^y in Model (1) are defined as follows:

$$R_i^x = \bar{x}_i - \underline{x}_i \text{ and } R_q^y = \bar{y}_q - \underline{y}_q \quad (3)$$

Thus, the efficiency score φ for OE can be derived as follows:

$$\varphi = 1 - \frac{\left(\sum_{i=1}^m \frac{d_i^{x*}}{R_i^x} + \sum_{q=1}^s \frac{d_q^{y*}}{R_q^y} \right)}{(m+s)} \quad (4)$$

where the subscript (*) denotes the optimality of Model (1) [40].

The EE of particular n th water company can be evaluated using the following RAM-DEA model:

$$\begin{aligned} & \max \frac{\left(\sum_{i=1}^m \frac{d_i^x}{R_i^x} + \sum_{p=1}^r \frac{d_p^b}{R_p^b} \right)}{(m+r)} \\ & \text{s.t.} \\ & \sum_{i=1}^k x_{ij} \lambda_{ij} - d_i^x = x_{in} \quad (i = 1, \dots, m) \\ & \sum_{j=1}^k b_{pj} + d_p^b = b_{pn} \quad (p = 1, \dots, r) \\ & \sum_{j=1}^k \lambda_j = 1, \quad \lambda_j \geq 0 \quad (j = 1, \dots, k) \\ & d_i^x \geq 0 \quad (i = 1, \dots, m) \\ & d_p^b \geq 0 \quad (p = 1, \dots, r) \end{aligned} \quad (5)$$

where d_p^b is the slack variable for undesirable outputs. Then the range, R_p^b in Model (5) is defined as follows:

$$R_p^b = \bar{b}_p - \underline{b}_p \text{ where } \bar{b}_p = \max\{b_{pj}\} \text{ and } \underline{b}_p = \min\{b_{pj}\} \quad (6)$$

Thus, the efficiency score θ for EE can be derived as follows:

$$\theta = 1 - \frac{\left(\sum_{i=1}^m \frac{d_i^{x*}}{R_i^x} + \sum_{p=1}^r \frac{d_p^{b*}}{R_p^b} \right)}{(m+r)} \quad (7)$$

The unified operational and environmental performance, i.e., ECOE, of the particular n th water company can be assessed using the following RAM-DEA model:

$$\begin{aligned} \max \quad & \frac{\left(\sum_{i=1}^m \frac{(d_i^{x+} + d_i^{x-})}{R_i^x} + \sum_{q=1}^s \frac{d_q^y}{R_q^y} + \sum_{p=1}^r \frac{d_p^b}{R_p^b} \right)}{(m + s + r)} \\ \text{s.t.} \quad & \sum_{i=1}^k x_{ij} \lambda_{ij} - d_i^{x+} + d_i^{x-} = x_{in} \quad (i = 1, \dots, m) \\ & \sum_{j=1}^k y_{qj} - d_q^y = y_{qn} \quad (q = 1, \dots, s) \\ & \sum_{j=1}^k b_{pj} + d_p^b = b_{pn} \quad (p = 1, \dots, r) \\ & \sum_{j=1}^k \lambda_j = 1, \quad \lambda_j \geq 0 \quad (j = 1, \dots, k) \\ & d_i^{x+} \geq 0 \quad (i = 1, \dots, m) \\ & d_i^{x-} \geq 0 \quad (i = 1, \dots, m) \\ & d_q^y \geq 0 \quad (q = 1, \dots, s) \\ & d_p^b \geq 0 \quad (p = 1, \dots, r) \end{aligned} \quad (8)$$

In this model, the slack variable associated with input is split into its negative and positive parts [36]. The efficiency score σ for ECOE is defined as follows:

$$\sigma = \frac{\left(\sum_{i=1}^m \frac{(d_i^{x+*} + d_i^{x-*})}{R_i^x} + \sum_{q=1}^s \frac{d_q^{y*}}{R_q^y} + \sum_{p=1}^r \frac{d_p^{b*}}{R_p^b} \right)}{(m + s + r)} \quad (9)$$

2.2. Influence of Environmental Variables on Eco-Efficiency Scores

In this section we describe the approach we used to get a better insight of what might drive the eco-efficiency of water companies. We regressed the eco-efficiency scores against a set of explanatory factors that were associated with topography, treatment complexity and density [10,41]. As the eco-efficiency scores are truncated between 0 and 1, we used Tobit regression to obtain reliable results [10,41–49]. The Tobit model was defined as follows:

$$\varphi_{j,t} = a_0 + a_j z'_{j,t} + \eta_j + \varepsilon_{j,t} \quad (10)$$

where $\varphi_{j,t}$ denotes the eco-efficiency of each water company j at any period t , a_0 is the intercept (constant) term, $z'_{j,t}$ is the vector of environmental variables of any water company j at any time. Moreover, in the above regression model, η_j captures water company's unobserved heterogeneity (e.g., managerial ability) which is uncorrelated with the environmental variables and is distributed following the standard normal distribution, and $\varepsilon_{j,t}$ is the error (noise) term that is normally distributed [10,41].

3. Case Study Description

The empirical application evaluates the OE, EE and ECOE of 10 WaSCs and 7 WoCs in UK during the 2011–2018 period. The economic regulator, the Water Services Regulation Authority (Ofwat), monitors the performance of water companies. Every five years it sets the revenues that the water companies are allowed to recover from customers by challenging and approving companies' business plans (price determinations) [50]. The data used in this study comes from Ofwat and companies' websites.

Following previous published evidence in the water sector (e.g., [13,51–53]) we chose the following inputs, desirable outputs and undesirable outputs. Two inputs were selected: (i) the water energy expenditure (costs) measured in millions of £ every year [10,41,54], and (ii) the other water expenditure (costs) [50]. This was calculated as the difference between water operating cost and water energy cost [10,41]. Other costs were measured in millions of £ per year [10,41]. The desirable outputs were defined as follows. We used the annual volume of drinking water delivered measured in megalitres [55–58]. The

second desirable output was defined as the annual number of water connected properties measured in thousands [59,60]. The undesirable output was presented by the GHG emissions from the process of water services [4,10,61–64]. They were expressed in tons of CO_{2eq} per year and are measured following the UK Government Environmental Reporting Guidelines [10,41,65].

Moreover, several studies in the past e.g., [51–53] stated that there might be several environmental factors that could impact on companies' performance. Consequently, we selected the following variables which were based on topography, water treatment complexity and density [41,66–68]. The variables used to capture topography included: (i) the water taken from boreholes measured in percentage [10,60,69]; (ii) the water taken from rivers measured in percentage [10,41,70], (iii) average pumping head as a proxy for the energy requirements to supply water to end-users [10,41,60]. We included two variables to capture treatment complexity: (iv) the water that gets advanced treatment measured in percentage (for more details please see [66–68,71] and (v) the number of treatment works required to treat water that comes from surface [41,71,72]. Finally, we included population density which was calculated as a ratio of water population and area [69–73]. Table 1 summarizes the descriptive statistics for the variables employed in the empirical application.

Table 1. Descriptive statistics.

Variables	Unit of Measurement	Mean	Std. Dev.	Minimum	Maximum
Water delivered	Ml/year	717	554	56	2169
Water connected properties	000 s/year	1490	1118	123	3826
Greenhouse gas emissions	tonCO _{2eq} /year	86,151	70,335	4542	275,900
Energy costs	£m/year	19.72	14.58	1.51	59.99
Other costs	£m/year	91.17	75.85	7.56	331.65
Water taken from rivers	%	27.8	24.8	0.0	85.7
Water taken from boreholes	%	41.0	31.5	0.5	100.0
Surface water treatment works	nr	15.043	15.075	1.000	54.000
Water receiving advanced treatment	%	93.0	5.4	81.0	100.0
Average pumping head	nr	138.911	36.937	64.820	224.210
Population density	000 s/km ²	0.462	0.275	0.146	1.250

4. Results and Discussion

4.1. Assessment of Operational Efficiency, Environmental Efficiency and Eco-Efficiency

Figure 1 reports the average estimates of the OE, EE and ECOE of the English and Welsh water industry during the years 2011–2018. The results indicated that, on average, water companies performed excellent from an operational perspective (i.e., by considering inputs and desirable outputs as variables) as the mean efficiency score was 0.972. This means that the UK water sector could further decrease its energy and other costs by 2.8% while expanding its water services by the same level to improve performance. However, this measure does not include the undesirable outputs. When carbon emissions are incorporated in the performance estimation, water companies reported lower efficiency scores from an environmental point of view. It is found that the potential savings for inputs and carbon emissions among water companies was approximately 14.6% on average. The combination of operational and environmental performance leads to the measurement of eco-efficiency. It is found that during the years 2011–2018 the mean ECOE was 0.783 which means that costs and carbon emissions could further reduce by 11.7% on average.

We next discuss the trend in the efficiency scores. OE followed a decreasing trend during the years 2011–2015 at a rate of 0.31% per year. This means that increases in energy and other costs had a negative impact on companies' OE. The situation changed the forthcoming years where the water industry appeared to have made gains in its efficiency. Compared to 2011, OE improved from 0.976 to 0.984 in 2018, an improvement by 0.82%. Dealing with carbon emissions was challenging for the industry. There was an increasing trend in EE during the years 2011–2015. EE was progressing at an annual rate of 0.16%

meaning that water companies were able to reduce costs and carbon emissions during that period. We also note that in 2011 the mean EE was already at high levels, 0.893 and small efficiency gains were achieved till 2015. However, a decreasing trend was apparent the following years which was attributed to increases in carbon emissions and production costs. It is noted that energy and other costs increased by 5% and 6%, respectively, which led to higher increases in overall costs. As a result, the use of more energy and other costs in the production costs might have a negative impact on carbon emissions which showed an increase of 10% compared to previous year. Overall, EE considerably reduced which means that the water companies needed to make more efforts to invest in new carbon technologies that could reduce GHG emissions. As for the trend in the ECOE scores, it appears that it was mainly driven from the EE. It follows an increasing trend during the years 2011–2015 as ECOE was increasing at a small rate of 0.42% per year on average. In the forthcoming years, it followed a decreasing trend due to an increase in the level of carbon emissions. Overall, the results indicated that eco-inefficiency in the English and Welsh water industry exists. A decreasing trend in ECOE was evident from 2015 onwards. Water companies should use new carbon efficient technologies to reduce production costs and carbon emissions. Moreover, it is of great importance to incorporate GHG emissions in the analysis to improve business decision making process.

Figure 1. Evolution of average operational efficiency (OE), environmental efficiency (EE) and eco-efficiency (ECOE) of English and Welsh water companies.

Since the sample evaluated in this empirical application consists of both WaSCs and WoCs, we report the efficiency scores by company type (Table 2). We divided the period into two sub-periods, i.e., 2011–2015 and 2016–2018 to relate the findings to the regulatory cycle. The results indicated that WaSCs performed better than WoCs when GHG emissions are included in the estimation. From an operational point of view, there was no difference in the efficiency scores between WaSCs and WoCs. Regardless of company type, there is room for improvement in terms of both OE and EE. In particular, during the years 2011–2018, the OE of WaSCs and WoCs was 0.972 which means that water companies needed to further reduce their costs and expand their water services by 2.8% on average. By contrast, lower EE and ECOE scores were reported. The mean EE of WaSCs and WoCs was 0.864 and 0.843 which means that costs and GHG emissions could further reduce by 13.60% and 15.74%, respectively. The results from the ECOE score indicated that average WaSC should further reduce costs and carbon emissions by almost 20% when trying to expand its water services. Moreover, the further increase in WoC's volumes of water delivered

and connected properties required the contraction of energy and other costs, and carbon emissions by almost 25% on average.

Table 2. Operational efficiency (OE) environmental efficiency (EE) and ecoefficiency (ECOE) for English and Welsh water and sewerage companies (WaSCs) and water only companies (WoCs).

Year	WaSCs			WoCs		
	OE	EE	ECOE	OE	EE	ECOE
2011	0.979	0.900	0.822	0.970	0.882	0.776
2012	0.965	0.911	0.835	0.961	0.892	0.787
2013	0.972	0.907	0.835	0.966	0.889	0.793
2014	0.962	0.910	0.832	0.965	0.888	0.785
2015	0.961	0.913	0.841	0.967	0.878	0.782
2016	0.980	0.819	0.773	0.977	0.816	0.749
2017	0.976	0.868	0.825	0.980	0.821	0.759
2018	0.982	0.684	0.658	0.987	0.676	0.614
2011–2015	0.968	0.908	0.833	0.966	0.886	0.785
2016–2018	0.979	0.790	0.752	0.981	0.771	0.708
Average	0.972	0.864	0.803	0.972	0.843	0.756

We turn now our discussion in the trend of the efficiency scores for WaSCs and WoCs and the regulatory cycle. During the first sub-period (2011–2015), which is the period covered by the 2009 price determination (price review), Ofwat adopted several schemes to incentivize water companies to improve operational and environmental performance. For instance, water companies were permitted to maintain any savings made in operating expenditure no matter which year they were made [74]. Furthermore, Ofwat introduced the Service Incentive Scheme (SIM), a set of several performance indicators related to quality of service and environment, and provided financial rewards for the companies who performed well [69]. The results indicated that there was an increasing trend in mean water companies' ECOE which takes into account both environmental and operational efficiency. WaSC and WoC's ECOE was increasing at an annual rate of 0.57% and 0.20%, respectively. In particular, WaSC's mean ECOE increased from 0.822 in 2011 to 0.841 in 2018, an increase of 2.72%, whereas WoC's mean ECOE improved from 0.776 in 2011 to 0.782 in 2018, an increase of 0.766%. Although these efficiency scores were among the highest ones achieved during the entire period, it demonstrates that WaSCs and WoCs still need to make considerable reductions in costs and carbon emissions to improve eco-performance. Moreover, during the same sub-period WaSC performed slightly better than WoCs from an operational point of view. However, the decrease in WaSCs' OE was higher than WoCs. In particular, average WaSC's OE was decreasing at an annual rate of 0.46% whereas the rate of decrease in average WoC's efficiency was at the level of 0.09%. We note that during the years 2014–2015, WoCs' mean OE was higher than the one reported by WaSCs which means that WoCs managed to make some gains in efficiency. However, OE focused on inputs and desirable outputs and did not include carbon emissions. When the latter is included in the analysis, then WoCs' efficiency is lower than WaSCs. It appears that WaSCs' mean EE was increasing at rate of 1.4% per year whereas WoCs' mean EE deteriorated. We note that during that period WaSCs reported high levels of EE, whereas WoCs did not perform well in their daily operations, in reducing production costs and carbon emissions.

We next analyze the results from the second sub-period (2016–2018) which is the period covered by the 2014 price review. During that period Ofwat maintained the rolling incentive mechanism adopted in the previous period (savings in operating expenditure) and replaced SIM with a new incentive scheme to monitor service quality and environmental performance. This scheme included a set of common and bespoke performance indicators that water companies needed to report every year. These indicators aimed to provide excellent quality of service at an efficient expenditure and to enhance sustainability of the industry. Examples include water leakage, unplanned interruptions, pollution

incidents, GHG emissions. Targets were set for each performance indicator that companies needed to achieve during the year or at the end of the regulatory period (Outcome Delivery Incentives—ODIs) [69]. If targets are met (outcomes are delivered), then water companies are rewarded financially (e.g., in case of water leakage) or in terms of reputation (e.g., in case of GHGs). If not, they are penalized. The findings from this study, indicated that the 2014 price review appeared to be challenging for both WaSCs and WoCs. If carbon emissions are ignored, then OE for both WaSCs and WoCs followed an increasing trend. OE was increasing at an annual rate of 0.71% and 0.67%, respectively. It also showed that WoCs showed higher levels of OE than WaSCs suggesting that gains in efficiency for WoCs were increasing over time. However, this picture is incomplete as it does not include undesirable outputs in the analysis. Consequently, during the years 2016–2018 the ECOE for WaSCs and WoCs was volatile and was mainly driven by changes in carbon emissions. When both OE and EE are taken into account, it is found that WaSCs performed better than WoCs. However, the ECOE for both types of companies was decreasing at an annual rate of almost 7%. Thus, during that period (2016–2018), water companies did not manage to improve their managerial practices leading to higher levels of carbon emissions released in the atmosphere. In particular, in 2018 the potential savings for costs (e.g., energy and other) and carbon emissions among WaSCs and WoCs were 34.6% and 38.6%, on average. Overall, the results indicated that although WaSCs were more eco-efficient than WoCs during the years 2011–2018, there is still room for improvements in their production process. Methods to reduce production costs and carbon emissions could be for instance the use of more efficient energy techniques when pumping water from different resources and the use of more renewable energy in the treatment process.

Table 3 reports the efficiency scores and the relevant rankings at a company level during the years 2011–2018. Several interesting conclusions can be drawn from these results. First, the number of water companies that were found to be eco-efficient were smaller than the ones from an operational point of view. For instance, five water companies (3 WaSCs and 2 WoCs) were 100% efficient from a production point of view. However, when GHG emissions were included in the analysis, only two companies (2 WaSCs) were 100% efficient. The other water companies were found to be considerably inefficient in terms of EE and ECOE. This finding evidences that reducing carbon emissions is challenging for most water companies. Moreover, the potential savings in costs from an operational point of view varied between 0% and 8.9% among companies. Nevertheless, considerable more savings were possible from an environmental point of view. These savings ranged from 0% to 23.4% on average over the whole period of study. There were several WaSCs with lower EE scores than WoCs which means that larger firms might not be more efficient than smaller ones. WaSCs' unified efficiency scores varied from 0.660 to 1.000 suggesting that the worst water company needed to curtail costs and carbon emissions by 34% while expanding output to catch-up with the most eco-efficient companies in the sample. In contrast, higher cost savings were possible for WoCs as their ECOE scores ranged from 0.650 to 0.842. Thus, while delivering more water to more customers, average WoCs could reduce production costs and GHG emissions between 15.8% and 35%.

4.2. Effect of Environmental Variables on Eco-Efficiency Scores

In order to comprehend what drives eco-efficiency of the UK water companies, we regressed the ECOE scores against a set of environmental factors. The findings are reported in Table 4. It is found that water taken from rivers and boreholes, advanced levels of water treatment, population density and the number of treatment works from surface water had a statistically important effect on eco-efficiency. Among these variables, advanced water treatment and population density had the major impact on eco-efficiency as indicated by the magnitude of the estimated coefficient. In particular, keeping other factors constant, one unit increase in the level of water treatment complexity, it would decrease eco-efficiency by 0.737 units on average. This result evidences that the more advanced the treatment of water is, the higher the costs of treatment could be. It illustrates the importance of developing and

implementing policies at watershed level to prevent water pollution and therefore, to avoid the use of advanced treatment to produce drinking water. In contrast, one unit increase in population density could lead to an increase in efficiency by 0.311 units on average. This finding suggests that delivering water to densely populated areas might require lower operating costs and GHG emissions. Moreover, it is found that when more water is abstracted from rivers and wells, it is likely that the use of pumps could be higher. This might result in higher carbon emissions and inefficiency. Finally, the higher the number of works to treat water from surface water resources the lower the costs of treatment could be. However, its impact on efficiency is immaterial as shown by the small magnitude of the estimated coefficient.

Table 3. Average operational efficiency (OE), environmental efficiency (EE) and eco-efficiency (ECOE) and ranking of English and Welsh water companies.

	Operational Efficiency		Environmental Efficiency		Eco-Efficiency	
	Score	Rank	Score	Rank	Score	Rank
WaSC1	0.986	7	0.766	17	0.679	13
WaSC2	0.891	17	0.831	11	0.694	12
WaSC3	1.000	1	0.844	8	0.786	8
WaSC4	0.941	15	0.863	7	0.841	5
WaSC5	0.969	11	0.782	14	0.660	15
WaSC6	0.999	6	1.000	1	1.000	1
WaSC7	1.000	1	1.000	1	1.000	2
WaSC8	1.000	1	0.982	3	0.984	3
WaSC9	0.973	10	0.766	16	0.644	17
WaSC10	0.963	13	0.807	12	0.739	11
WoC1	0.911	16	0.796	13	0.675	14
WoC2	0.963	14	0.837	9	0.740	10
WoC3	1.000	1	0.872	6	0.812	7
WoC4	1.000	1	0.873	5	0.825	6
WoC5	0.979	9	0.912	4	0.842	4
WoC6	0.964	12	0.774	15	0.650	16
WoC7	0.984	8	0.833	10	0.746	9

Table 4. Estimated results from the regression model to identify drivers of eco-efficiency.

Variables	Coef.	Std. Err.	z-Stat	p-Value
Constant	1.331	0.282	4.720	0.000
Water abstracted from rivers	−0.084	0.043	−1.940	0.052
Water abstracted from boreholes	−0.058	0.034	−1.720	0.085
Advanced water treatment	−0.737	0.286	−2.580	0.010
Average pumping head	0.000	0.000	−0.780	0.437
Population density	0.311	0.110	2.840	0.005
Number of SW treatment works	0.008	0.002	3.150	0.002
Year				
2012	0.018	0.018	1.010	0.311
2013	0.023	0.018	1.280	0.202
2014	0.012	0.018	0.660	0.507
2015	0.018	0.018	1.040	0.298
2016	−0.046	0.018	−2.600	0.009
2017	−0.003	0.018	−0.160	0.869
2018	−0.170	0.021	−8.180	0.000
Log-likelihood	148.480			
Wald X ² (13)	250.190			
p-value	0.000			
No of obs	136			

Dependent variable = efficiency score; Bold statistics are statistically significant at 5% significance level; Bold and italic statistics are statistically significant at 10% significance level.

The findings of our approach can be of great importance to policy makers. First, our approach gives them the opportunity to evaluate the performance of water companies from three perspectives namely: operational efficiency (OE), environmental efficiency (EE) and eco-efficiency (ECOE). Although water companies might do well in terms of operational efficiency, this might not be the case when GHG are included in the analysis. Actually, the empirical application has showed that if GHG emissions were ignored, water companies reported high levels of OE. However, if GHG emissions are incorporated in the estimation process, then the potential savings in costs and GHG emissions are substantial. This finding suggests that reducing GHG emissions is challenging for the water companies. Thus, policy makers need to be aware of not only their OE but also their ECOE when making decisions on how to operate their assets. Moreover, our analysis showed that there might be several operating characteristics that might impact water companies' eco-efficiency such as water treatment complexity and density. Including these factors in water companies' managerial practices could help them make informed decisions.

5. Conclusions

The path towards a sustainable and carbon neutral water cycle requires information on how water companies perform both from a production and environmental point of view. This can be done by assessing the efficiency of the water supply process, the ability of a water company to reduce its costs and carbon emissions while trying to expand its output (drinking water service). In this study, it is employed, for the first time, the non-radial RAM-DEA approach to estimate the OE, EE and ECOE of several water companies in England and Wales. The further use of regression techniques permitted us to determine the effect of several environmental variables on companies' eco-efficiency.

The main points can be summarized as follows. First, it is found that during the years 2011–2018, on average, water companies reported high OE scores, 0.972. This means that while delivering more water to more customers, companies needed to further reduce energy and other costs by 2.8%. However, when GHG emissions were incorporated in the analysis, efficiency scores obtained lower values. From an environmental point of view, the savings for costs and GHG could reach the level of 14.6% on average. Moreover, the mean ECE score was 0.783 which means that while expanding water services, companies could further reduce costs and GHG emissions by 11.7% on average. Thus, the findings indicate that eco-inefficiency exists. Water companies need to considerably improve their managerial practices by adopting new technologies that could allow them to decrease production costs and carbon emissions. Our results also showed that WaSCs were more eco-efficient than WoCs. The potential savings in costs and GHG emissions while delivering more water to customers could be almost 20% among WaSCs and 25% among WoCs on average. A downward trend in the WaSCs and WoCs eco-efficiency scores was apparent from 2016 onwards suggesting that reducing carbon emissions during the 2014 price review was challenging. The regulator could interfere by designing policies that could incentivize the water companies to adopt new environmentally technologies such as the use of renewable energy in the water treatment process. Factors that could have a major influence on water companies' eco-efficiency included advanced levels of water treatment, water taken from rivers and boreholes and population density.

The following policy implications can be discussed based on the findings of our study. First, our results demonstrated that regulated water companies need to act to improve their eco-efficiency. This can be achieved by making reductions in both production costs and carbon emissions. Examples might include the use of more energy efficient techniques when pumping water from different water resources or employing pumps more closely adjusted to the required need. Another example could include the use of renewable energy during the treatment of water which could reduce the use of energy and its costs. This could consequently result in lower GHG emissions released to the atmosphere. The water regulator could design and introduce policies that could incentivize water companies to use carbon neutral technologies in the production process. Moreover, our study showed

that there might be other operating characteristics that could impact water companies' eco-efficiency. For instance, the more advanced the treatment of water is the higher the energy costs and carbon emissions could be. Thus, ensuring that the water abstracted from different water resources is clean should be of great significance. Densely populated areas might require shorter pipes to connect and move water so operating costs and levels of carbon emissions might be lower. These factors should be considered in the business making decision process as they could lead to an eco-efficient water industry. Overall, we believe that our approach could be of great interest to policy makers at they can evaluate the economic and environmental efficiency of the water abstraction, treatment and supply process. Our method can help managers and regulators to make robust comparisons among the water utilities assessed and quantify the savings that could be achieved in terms of operating costs such as energy and other costs, and in terms of greenhouse gas emissions. Moreover, policy makers could identify best and worst performers in the industry and introduce incentives to enhance efficiency such as financial penalties when economic and environmental targets are met. We finally note that policy makers could further get a better insight what drives eco-performance in the water cycle. In particular, the adoption of innovative solutions such as the use of renewable energy to reduce the costs of advanced water treatment could enhance eco-efficiency. We believe that the above topics could enable managers to make the right economic and environmental decisions that could lead to a greener economy and society.

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