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Carbon efficiency analysis in the provision of drinking water: Estimation of optimal greenhouse gas emissions

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ABSTRACT

Assessing carbon efficiency (CE) in the provision of drinking water services is essential to achieve a net-zero greenhouse gas (GHG) urban water cycle. Previous studies evaluating the CE of water companies are very scarce and employed parametric and non-parametric. Both methodological approaches present limitations such as overfitting issues or require assumptions about the production technology which could lead to less reliable efficiency scores. To overcome these limitations, in this study, and for the first time, we estimated CE of English and Welsh water companies using the Efficiency Analysis Trees (EAT) approach. This technique brings together machine learning and non-linear programming techniques to estimate production frontier and efficiency scores. It also allowed us to quantify the optimal level of GHG emissions in the provision of water services and estimate potential GHG savings. Bootstrap truncated regression methods were employed to quantify the impact of operating characteristics on CE of water companies. The optimal level of GHG emissions was estimated to be between 0.062 and 133.03 tons of CO_2 equivalent (CO_{2eq}) per year and per connected property. The average CE was at the level of 0.632. This means that GHG emissions could reduce by 36.8% to maintain the same level of water services. Equivalently, this corresponds to a reduction of 488,321 tons of CO_{2eq} per year. Water only companies exhibited a better performance than water and sewerage companies with an average CE of 0.785 and 0.540, respectively. The performance of the English and Welsh water companies decreased over time. In 2011 the average CE was 0.772 whereas it went down to 0.534 in 2020. It was also estimated that on average water companies could reduce 0.034 tons of CO_{2eq} per cubic meter of drinking water supplied and 16.16 tons of CO_{2eq}/connected property per year. The regression results showed that topography and water treatment complexity had a significant impact on CE. The conclusions of this study are relevant for policy makers to define policies toward a low-carbon urban water cycle.

1. Introduction

Access to drinking water is recognized as a human right by United Nations (2011). However, the provision of drinking water involves energy intensive activities (Rodríguez-Merchan et al., 2021) which are relevant within the water-energy nexus (Li et al., 2019; Xu, 2020; Fontenelle et al., 2022). The energy used to provide drinking water services involves the emission of greenhouse gas (GHG) (Rothausen and Conway, 2011; Jin and Kim, 2019). Cutting down GHG emissions will bring huge benefits to environment and people's health. In addition to this, controlling GHG emissions in the provision of water services could have a positive effect on customers by reducing water bills (Heims and Lodge, 2018). The use of renewable energy during the water treatment process could lead to lower energy costs and GHG emissions. These cost savings should be passed to customers in terms of lower water tariffs (Strazzabosco et al., 2020).

Over the years, policy makers have been making efforts to tackle economic and environmental sustainability of the urban water cycle. For instance, the United Nations (2015) pointed out the significance of renewable energy, sustainable use of energy (Goal 7) and of reducing

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GHG emissions to deal with climate change (Goal 13). They also highlighted the need of all people to have access to clean and safe water services at an affordable cost (Goal 6). The water-energy-GHG nexus is at the forefront towards realising a sustainable and carbon-free water industry by researchers and policy makers. Consequently, this topic has generated growing interest in the published literature, providing interesting guidelines for policy makers.

Past research evaluating carbon efficiency (CE) of water companies have used parametric approaches (Molinos-Senante and Maziotis, 2022) such as Stochastic Frontier Analysis (SFA) and non-parametric methods (Data Envelopment Analysis, DEA) (Molinos-Senante et al., 2022b; 2022b). As we discuss in the literature review section, both approaches present restrictions which limit the assessment of CE of water companies. Alternative methods to DEA and SFA for estimating efficiency scores are those that apply Kernel-based approaches and local regression techniques. For example, Du et al. (2013) proposed a kernel smoothing method that can handle multiple shape constraints (e.g., monotonicity) for multivariate functions. Parmeter et al. (2014) evidenced how constraint weighted bootstrapping may be applied to impose smoothness conditions on linear estimates. Alternatively, Kuosmanen and Johnson (2010) showed that DEA may be reinterpreted as non-parametric least-squares regression subject to shape constraints on the production frontier and sign constraints on residuals. However, none of the above methodologies for computing efficiency scores address the problem through machine learning techniques, despite their advantages (Esteve et al., 2021).

Unlike previous methodological approaches discussed to estimate efficiency scores, i.e., DEA, SFA, Kernel-based approaches and local regression techniques, the Efficiency Analysis Trees (EAT) approach, brings together machine learning and frontier analysis to estimate efficiency scores. EAT was developed by Esteve et al. (2020) and uses Classification and Regression Trees (CART) techniques, developed by Breiman et al. (1984), to measure the frontier level or the optimum level of the predicted variable (GHG emissions in this study). It further uses linear programming techniques to construct the production frontier and generate efficiency scores. Moreover, the EAT approach imposes the free disposability assumption and adjusts the regression trees to estimate production frontiers and measure efficiency (Esteve et al., 2022). The production frontier that is constructed using the EAT approach takes the form of a step function. Esteve et al. (2020, 2021) demonstrated that the EAT method outperforms non-parametric approaches both in terms of mean squared error and bias. The authors pointed out that the new approach enhances robustness of model results and accuracy of efficiency because it does not suffer from overfitting. Moreover, EAT, unlike SFA and DEA, allows estimating the optimal level of GHG emissions. This issue is very relevant from a policy perspective towards a carbon neutral urban water cycle. For the above reasons, we selected the EAT approach to compute CE of water companies.

Within this context the objectives of this study are fourfold. The first objective is to evaluate the CE of drinking water services in terms of reducing GHG emissions using the EAT methodological approach. The second objective is to estimate the optimal level of GHG emissions in the provision of water services according to the number of connected properties and volume of drinking water delivered by water companies. The third objective is to quantify potential GHG savings of water utilities. The fourth objective is to get a better insight on what drives CE in water services, i.e., assess the influence of operational characteristics of water companies on their CE.

The contribution of this study to existing literature is as follows. For the first time, a method that combines machine learning and production economics is employed to measure the CE of drinking water services. This is a pioneering approach because to the best of our knowledge there have not been any studies in the literature that measured CE in the water industry using the EAT approach overcoming the limitations of DEA and SFA approaches. Moreover, this methodological approach allows quantifying the optimal level of GHG emissions which is relevant to define GHG reduction targets by water regulators. Furthermore, the use of bootstrap regression techniques allows us to get a better insight on how operating characteristics impact CE when providing water services. CE has been estimated for a sample of water companies in England and Wales over the 2011–2020 period.

2. Literature review about carbon efficiency assessment

Water-energy-carbon nexus within the urban water cycle has been investigated using different approaches: i) Most of the past research on this topic focused on quantifying GHG emissions associated with the provision of drinking water and wastewater services (e.g., Chen et al., 2018; Wakeel et al., 2018; Liao et al., 2020). By using life cycle analysis tools, input-output models or mixed models, previous studies quantified the energy used and GHG emitted in the provision of water and treatment of wastewater (Venkatesh et al., 2014; Santos et al., 2015; Samanaseh et al., 2017; Lam and Van Der Hoek, 2020); ii) Other studies evaluated the economics of reducing GHG emissions within the urban water cycle (e.g., Zhang et al., 2017; Fane et al., 2020; Ortiz et al., 2021; Alix et al., 2022).

Focusing on the performance assessment of water utilities in the provision of drinking water, past research integrating carbon emissions is much more limited. On the one hand, some studies focused on evaluating the impact of considering GHG emissions in the operational performance of water companies (Ananda and Hampf, 2015; Ananda, 2018, 2019; Molinos-Senante and Maziotis, 2021). These studies evaluated the efficiency of water companies in the provision of water and sanitation services under two scenarios: i) ignoring GHG emissions from the operation of facilities and ii) including GHG emissions as a subproduct. The comparison of efficiency scores under both approaches allows estimating the impact of integrating GHG emissions in the performance assessment of water utilities. On the other hand, other studies assessed the eco-efficiency of water companies integrating GHG emissions as undesirable outputs (Sala-Garrido et al., 2021a, 2021b; Mocholi-Arce et al., 2022; Amaral et al., 2022; Molinos-Senante et al., 2022a). These studies computed a synthetic index (eco-efficiency index) that integrates the operational costs, volume of drinking water supply (and its quality) and carbon emissions of water companies. Hence, the eco-efficiency index provides relevant information about the performance of water companies from a holistic perspective since eco-efficiency estimation integrates operational, economic, and environmental variables. However, it does not allow evaluating the carbon performance of water companies. In other words, these previous studies did not estimate an individual synthetic index for assessing the performance of water companies in terms of GHG emissions.

To the best of our knowledge, a small number of recent studies (Molinos-Senante et al., 2022b; Molinos-Senante and Maziotis, 2022) assessed the CE of water companies in the provision of water services. Unlike past research evaluating eco-efficiency of water companies, these studies computed a performance index focused only on GHG emissions. In a second stage of analysis, the authors identified main external variables influencing the carbon performance of water utilities. In spite of their remarkable novelty and contribution to the water-energy nexus strand of literature, past research on this topic presents some methodological limitations. On the one hand, Molinos-Senante et al. (2022b) employed DEA to estimate CE scores. It is a non-parametric approach based on linear programming models. DEA is a deterministic method and therefore, does not take into account noise. Consequently, any deviations from the efficient frontier are simply attributed to inefficiency (Ferreira and Marques, 2017). Esteve et al. (2020, 2021, 2022) showed that the DEA approach suffers from overfitting issues which could lead to less reliable efficiency scores. On the other hand, Molinos-Senante and Maziotis (2022) estimated CE scores using the SFA approach which requires an assumption about the underlying production technology (e.g., translog) of water companies. Moreover, inefficiency is subject to different assumptions regarding its distribution such as half-normal, exponential, gamma (Letti et al., 2022). Thus, efficiency scores are sensitive to these assumptions which could lead to different estimates and policy conclusions. Both methodological approaches (DEA and SFA) have therefore limitations making the efficiency scores less robust. Hence, past research evaluating CE of water companies present some methodological restrictions that limits their use for better understanding carbon performance of water companies.

3. Material and methods

3.1. Carbon efficiency estimation

This section outlines the EAT method which has been employed to measure the CE of water companies in the provision of drinking water. We use this technique because unlike parametric techniques, it does not require a priori assumption about the production frontier. Unlike other non-parametric techniques, EAT does not suffer from overfitting uses. Thus, it improves robustness of model results and improves decision making process. Unlike parametric and non-parametric methods, it uses regressions trees to generate the optimum level of GHG emissions based on thresholds of the predictor variables.

The EAT approach is based on decision trees where the entire sample (water companies) is broken up into several nodes (non-overlapping regions) based on a set of thresholds of the predictor variables (volume of drinking water and water connected properties) (Rebai et al., 2020; Esteve et al., 2022) (see Fig. 1). The decision tree ends at terminal nodes which displays the estimated value of the predicted variable (GHG emissions in this case study) (Esteve et al., 2022). Because, the EAT approach imposes the free disposability assumption, the estimated value is not the average but the frontier, i.e., optimal value. Thanks to this property, EAT allows estimating the optimal level of GHG emissions of water companies. Nevertheless, the EAT approach further extends the CART method by employing the concept of free disposability and the use of efficiency analysis methods to estimate production frontiers (Valero-Carreras et al., 2021).

We assume that a dataset consists of a vector of predictor variables defined as $x_1, \ldots, x_m$ where $x_i \in R^m$ that is employed to predict a set of response variables denoted as $y, \ldots, y_n$ where $y_i \in R^n$. The EAT approach picks a predictor variable j and a threshold $s_j \in S_j$ where S_j is the set of possible thresholds for the variable j to break up the data into two nodes, t_R and t_L (Esteve et al., 2021). The best combination of predictor variables and thresholds is selected by minimizing the sum of the mean square error (MSE) of the two generated child nodes. It is as follows:

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

where n denotes the size of the sample, $R(t)$ is the MSE of each node t, t_L and t_R are the left and right nodes of the tree, respectively, $y(t_L)$ and $y(t_R)$ are the estimated values of the predicted variable (e.g., GHG emissions) for the left and right node of the tree, respectively (Esteve et al., 2020). The generic form of a regression tree is depicted below:

We note that the estimated predicted values of the response variable for the left and right node of the tree, $y(t_L)$ and $y(t_R)$ respectively are derived as follows:

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

$$y(t_R) = y(t) \tag{3}$$

where T is the sub-tree that is generated using the EAT method, k denotes the number of splits, $y(I_{T(k|t^* \rightarrow t_L,t_R)}(t_L))$ and $y(I_{T(k|t^* \rightarrow t_L,t_R)}(t_R))$ is the set of leaf nodes of the tree produced after executing the k-th split that Pareto dominates node t_L and t_R. Hence, $y(t_L)$ and $y(t_R)$ are frontier (optimal) values (Esteve et al., 2022). In brief, the Pareto dominance concept can be illustrated in Fig. 2. Let's assume that there are two inputs, x_1 and x_2. Node t' Pareto-dominates node t because $a^{t'} = (2,2) < b = (9,9)$ where a and b represent points of nodes t' and t, respectively. Node t' "is preferable to" node t because node t' uses less inputs than node t (Esteve et al., 2020).

Cross-validation techniques are used to select the best regression tree avoiding overfitting issues and therefore, the EAT approach estimates the following production technology (Esteve et al., 2020):

$$\widehat{PT}_{T_k} = \left\{(x, y) \in R_+^{m+1} : y \leq d_{T_k}(x)\right\} \tag{4}$$

where $d_{T_k}(x)$ is the predictor estimator with regards to the sub-tree T_k.

The CE of each water utility, based on the EAT method, is estimated by solving the following linear programming model:

$$\rho_{CE}^{EAT}(x_k, y_k) = \min \rho \tag{5}$$

subject to:

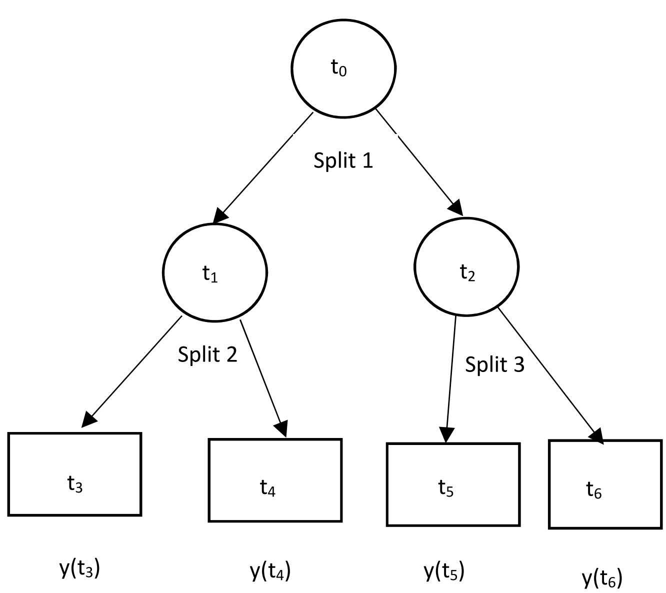

Fig. 1. Example of a regression tree applied to estimate carbon efficiency scores.

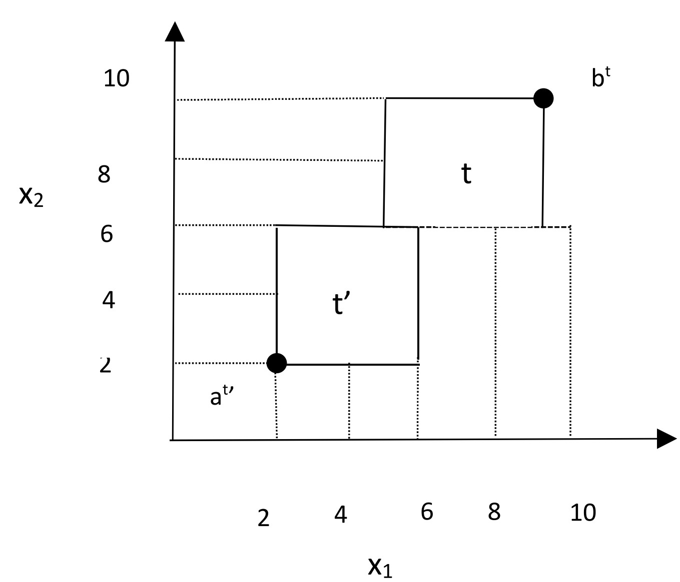

Fig. 2. Example of Pareto-dominance nodes.

$$\sum_{\substack{t \in \widetilde{T^*}}} \lambda_t a_j^t \leq \rho x_{jk}, j = 1, \dots, m$$

$$\sum_{\substack{t \in \widetilde{T^*}}} \lambda_t d_{rT^*}^t (a^t) \geq y_{rk}, r = 1, \dots, s$$

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

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

where ρ_{CE}^{EAT} is the CE score, $(a^t, d_{T^*}(a^t))$ are points in the input-output space for all $t \in T^*$, in which * denotes the final sub-tree, and λ are intensity variables used to construct the efficient frontier. A unit, i.e., water company, is carbon efficient, if and only if, $\rho_{CE}^{EAT} = 1$. By contrast, the water company has room to reduce carbon emissions if $\rho_{CE}^{EAT} < 1$. Potential savings in GHG emissions are estimated as follows:

$$GHG_s = GHG_c * \left(1 - \rho_{CE}^{EAT}\right) \tag{6}$$

where GHG_s are potential GHG savings if the water company is carbon efficient and GHG_c are current levels of GHG emissions of the water company evaluated.

The final step of our analysis involves analyzing the factors that could influence the CE of water companies. In doing so, the CE scores obtained using the EAT method (ρ_{CE}^{EAT}) are regressed against a set of operating characteristics of the water companies. In particular, and considering that CE scores take a value between zero and one, a bootstrap truncated regression approach is applied (Simar and Wilson, 2007). It should be noted that traditional Tobit regression may cause biased estimates due to the fact that efficiency scores, error term and operating characteristics may be serially correlated (Simar and Wilson, 2007).

The regression model is as follows:

$$\rho_{CE}^{EAT} = \beta_0 + \beta_i \xi_i^{'} + time + \varepsilon_i \tag{7}$$

where ρ_{CE}^{EAT} is the CE score derived from the EAT method (Eq. (5)), β_0 is the intercept, $\xi_i^{'}$ is the vector of operating characteristics of any water company i, t denotes time and β_i are estimated parameters. Finally, ε_i captures error and follows the standard normal distribution.

3.2. Case study

CE performance was estimated for a sample of 20 English and Welsh water companies embracing both Water only Companies (WoCs) and Water and Sewerage Companies (WaSCs) during the 2011–2020 period. Hence, our study involves 160 observations, i.e., company-year units. The empirical application focused on the provision of drinking water services, excluding sewerage activities because WoCs do not carry out this stage of the urban water cycle. As in many countries, the English and Welsh water companies are private natural monopolies and their economic and environmental performance is monitored by the Water and Services Regulation Authority (Ofwat) (Walker et al., 2021). Ofwat ensures that customers' bills are affordable and water companies are financially stable to provide services to customers, while environmental sustainability is maintained. Every five years Ofwat determines companies' future revenue allowances by approving their business plans (price review process).

Variables to estimate the CE of water companies were selected based on past research (e.g., See, 2015; Cetrulo et al., 2019; Goh and See, 2021) and data availability. Because, this study focused on CE estimation, GHG emissions is a very relevant variable to be considered. GHG emissions are an undesirable output to be minimized. In this context, Halkos and Petrou (2019) identified four main approaches to deal with undesirable outputs in efficiency assessment: i) ignoring them from the production function, ii) treating them as regular inputs, iii). Treating them as normal outputs and iv) performing necessary transformations to take them into account. Each methodological approach has its benefits and drawbacks and therefore, the selection of the method will depend on the research conducted. In this case study, EAT method was employed to estimate CE scores and therefore, GHG emissions were treating as inputs since water companies should minimize their production to improve their carbon performance. Although this approach is very simple, it has some appealing features and has been widely used in various applications (Li et al., 2022).

According to Ofwat (2010a, 2010b) and Molinos-Senante and Maziotis (2021a), GHG emissions were expressed in tons of CO_2 equivalent (CO_{2eq}) per year. Their measurement is based on the United Kingdom Government Environmental Reporting Guidelines (HM Government, 2019). The outputs used in the study were defined as follows. The first output was the volume of drinking water delivered in megalitres per year. The second output was defined as the number of water connected properties measured in thousands.

Regarding operational characteristics or environmental variables affecting CE of water companies, based on available data, the following variables were assessed: i) average pumping head which captures the energy intensity of the water abstraction, treatment and distribution process (Brea-Solis et al., 2017); ii) percentage of raw water taken from boreholes; iii) percentage of raw water taken from reservoirs (Villegas et al., 2019); iv) percentage of raw water that receives high levels of treatment before its distribution to final customers (Ofwat, 2019); v) number of treatment works undertaken when water comes from surface; vi) number of treatment works undertaken when water comes from groundwater resources (Walker et al., 2019) and; vii) population density defined as the annual number of water population divided by the area of water service (Sala-Garrido et al., 2021a). We finally used a time trend to capture the temporal nature of our study.

Table 1 reports the descriptive statistics of the variables used in this case study to assess the CE of water companies.

4. Results

4.1. Optimum level of greenhouse gas emissions

The frontier level of GHG emissions in the provision of drinking water services by English and Welsh water companies is shown in Fig. 3.

Table 1
Descriptive statistics of the English and Welsh water companies.

Variables	Unit of measurement	Mean	Std. Dev.	Min.	Max.
Greenhouse gas emissions	tons CO_{2eq}/year	82,689	67,135	3123	275,900
Water connected properties	000s	1578	1115	279	4047
Volumes of water delivered	Ml/year	750	548	140	2169
Average pumping head	Nr	138	34	65	201
Water taken from reservoirs	%	33.4	25.0	0.0	83.3
Water taken from boreholes	%	41.8	30.1	0.5	92.1
Number of surface water treatment works	Nr	17	15	1	54
Number of groundwater treatment works	Nr	53	39	7	127
Water receiving high levels of treatment	%	57.0	22.0	22.0	99.0
Population density	000s/km2	0.48	0.29	0.15	1.26

Observations: 160.

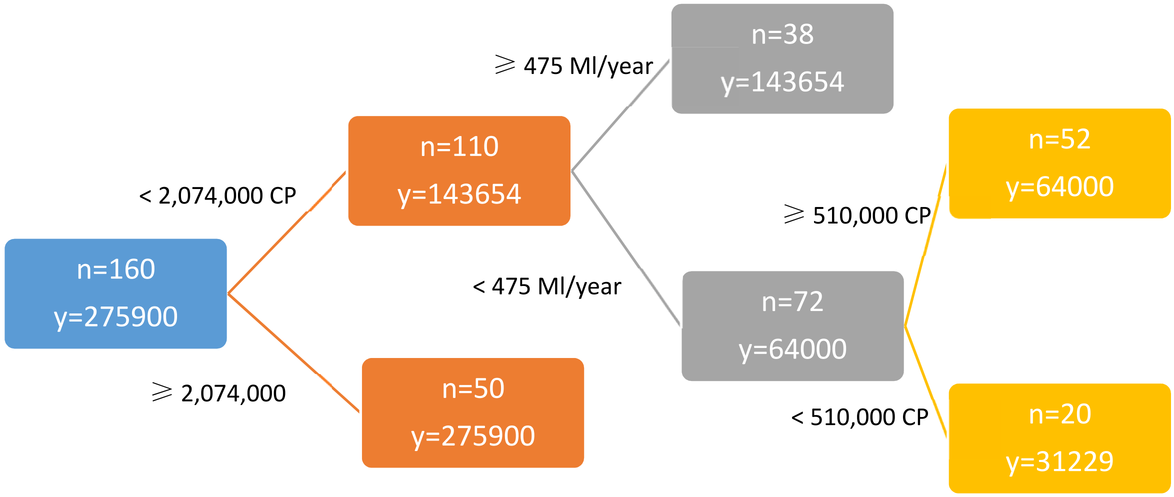

Fig. 3. Estimation of optimal levels of greenhouse gas emissions according to regression tree from efficiency analysis trees algorithm
* where n is the number of observations and y is the optimal level of GHG emissions in tons of CO_{2eq}/year and CP are connected properties.

According to Eq. (1), the regression tree shows the predictor that the split was based on and the frontier value of the response variable, which is the GHG emissions in our case study. The results indicate that both the volume of drinking water and water connected properties influenced the release of GHG emissions in the atmosphere. The optimum level of GHG emissions (i.e., frontier level) is 275,900 tons of CO_{2eq}/year when the number of connected properties is higher than 2.074 million. It means that the maximum GHG emissions for each connected property are 133,03 tons of CO_{2eq}/year. Moreover, if the number of water connected properties is less than 2.074 million and the volume of drinking water delivered to these properties is more than 475 ML per annum (475,000 m^3/year), then the optimum level of GHG is 143,654 tons of CO_{2eq}/year. Hence, in this case, the minimum GHG emissions per water connected property are 69.26 tons of CO_{2eq}/year and the maximum level of GHG emissions per cubic meter of drinking water is 0.302 tons of CO_{2eq}/year. An alternative node corresponds to supply less than 475,000 m^3/year of drinking water to a lower number of connected properties, between 2.074 million and 510,000. In this case, the optimum level of GHG emissions is 64,000 tons of CO_{2eq} per year. It suggests that optimum GHG emissions are larger than 0.302 tons of CO_{2eq}/year. Finally, the frontier level of GHG emissions for water companies providing drinking water to less than 510,000 connected properties is 31,229 tons of CO_{2eq} per year which involves a maximum of 0.062 tons of CO_{2eq}/year per connected property.

4.2. Carbon efficiency assessment

The next step of our analysis is to calculate the CE using Eq. (5) described in the methodology section. The results indicate that on average the English and Welsh water industry showed high levels of carbon performance during the years 2011–20 since the average CE was 0.632 which means that the industry could cut down GHG emissions by 36.8% to deliver the same level of water services (Table 2). Moreover, it is revealed that only 5 out of 160 observations (3.125%) were carbon efficient, i.e., their CE scores were 1.000. Therefore, they are the best performers in terms of GHG emissions. On average, as it is shown in Table 2, WoCs performed better than WaSCs. It is illustrated that average WoC's CE was 0.785 which suggests that on average, GHG could go down by 11.5%. In contrast, WaSCs reported considerably lower levels of CE. In particular, average WaSCs should cut down GHG emissions by almost 46% to maintain the same level of drinking water service. Moreover, in the case of WaSCs, only 1 out of 100 observations (1.000%) was identified as carbon efficient whereas the percentage of WoCs whose CE score was 1.000 was 6.667%. Both, WaSCs and WoCs need to make substantial efforts to improve its environmental performance which is evidenced according to the minimum CE scores estimated, 0.104 and 0.314 for WaSCs and WoCs, respectively. This means that the WaSC and WoC whose environmental performance is the worst could reduce GHG emissions by 89.6% and 68.6%, respectively.

Table 2
Summary statistics of carbon efficiency of English and Welsh water companies.

	Mean	Std. Dev.	Minimum	Maximum	Carbon efficient units (%)
All	0.632	0.253	0.104	1.000	3.125
WaSCs	0.540	0.235	0.104	1.000	1.000
WoCs	0.785	0.205	0.314	1.000	6.667

The CE scores from this study cannot be compared directly with the results of past research due to the study periods being analyzed are different and the methodological approaches and variables employed are also divergent. However, it is worth considering the findings of previous studies to contextualize the performance of the water companies evaluated in this study. Molinos-Senante et al. (2022b) using the DEA method estimated that the average CE of English and Welsh water companies from 2013 to 2018 was 0.497 with WaSCs being slightly more efficient than WoCs. By contrast, Molinos-Senante and Maziotis (2021a) reported larger CE scores for the English and Welsh water companies. The period considered by these authors was 2010–2019 and the average CE estimated was 0.925. These previous studies evidence the role of the methodology and variables used to estimate CE of water companies.

Fig. 4 depicts the distribution of CE scores across companies over the period of study. It is shown that the majority of observations related to WoCs reported an average CE which was higher than 0.81. This means that there were several cases where WoCs showed high levels of environmental performance. However, there were several observations where carbon performance was of concern. For instance, during the period of study 11 observations for WoCs reported a CE which ranged between 0.41 and 0.60. This means that on average WoCs could cut down GHG emissions between 40% and 59%. We note that there were 3 observations whose average CE was considerably lower, i.e., between 0.21 and 0.40. The potential savings in GHG could reach the level of 80% to deliver the same level of water services. Hence, both the water regulator and water companies should carry out a more detailed study to identify the specific causes of this poor CE and adopt the corresponding measures to improve its environmental performance. As far as WaSCs are concerned, and unlike WoCs, the majority of the observations

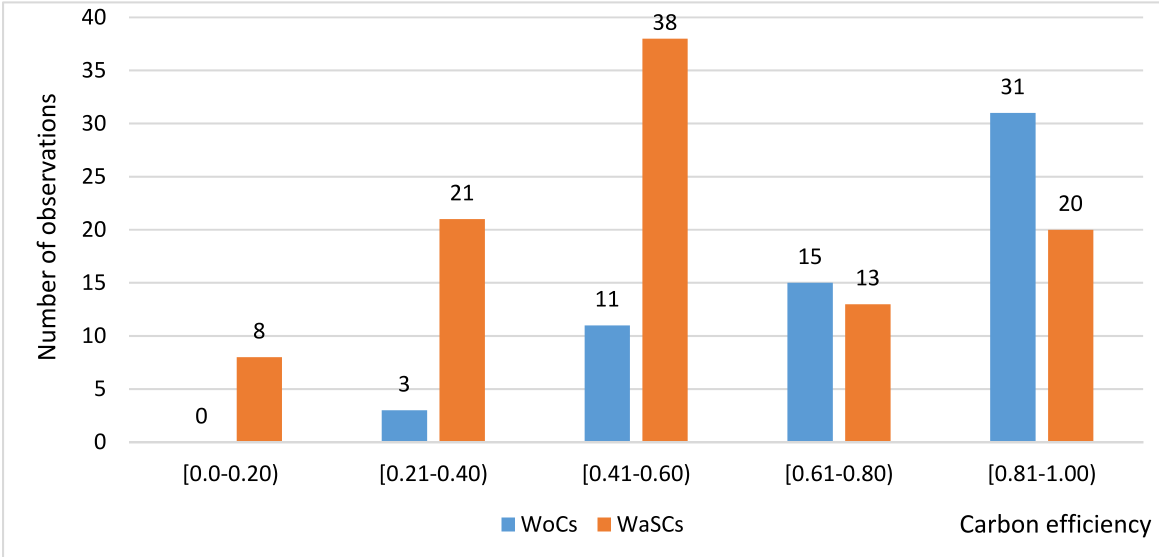

Fig. 4. Histogram of distribution of average carbon efficiency scores for water and sewerage companies (WaSCs) and water only companies (WoCs) in England and Wales.

reported an average CE which ranged between 0.41 and 0.60. Nevertheless, there were several cases where WaSCs' environmental performance was very poor since average CE score was lower than 0.20 indicating that those WaSCs could save more than 80% of their current GHG emissions. By contrast, there are 20 observations associated with WaSCs reported high levels of CE, i.e., larger than 0.81.

To get a better understanding on how CE changed over time, we looked into its trend over the years 2011–2020 (Fig. 5). Result should be interpreted with caution because only a production frontier was estimated embracing data from 2011 to 2020 rather than a yearly frontier. The results are also split into two sub-periods, 2011-15 and 2016-20, so that they can be linked with the regulatory cycle in the English and Welsh water industry. It is found that on average the industry presented a downward trend in the CE suggesting that environmental performance deteriorated over time. On average, the CE dropped by 30%, from 0.772 in 2011 to 0.534 in 2020. This means that industry needs to put considerable efforts to reduce GHG emissions to deliver the same level of water services.

Both WoCs and WaSCs reported a deterioration in their carbon performance over time. During the first years of the study, WoCs were doing well in terms of environmental performance. In 2011, average WoC showed a CE score of 0.912 which means that GHG emissions could go down by 8.8%. In the following years, CE, although was at high levels, started to fall. We note that during the years 2011–15, the CE was going down at an annual rate of 3.4% on average. However, average WoC reported a CE of 0.843. This sub-period refers to the 2009 price review period. As part of the price review, the regulator introduced several incentive schemes to encourage companies to improve performance. For instance, companies were allowed to keep any savings in operating expenditure regardless of the year they were made (Villegas et al., 2019). Companies might have difficulties to control operating costs which reflected to their environmental performance as well. A downward trend in carbon performance was evident for WaSCs as well. It is shown that average WaSC reduced its efficiency from 0.632 in 2011 to 0.584 in 2015, an annual reduction of 1.9%.

The environmental performance for both WoCs and WaSCs continued to deteriorate during the second sub-period of our study (2016-20) which refers to the 2014 price review. During that period, the water regulator introduced financial penalties and rewards when companies achieved targets and delivered the outcomes they promised in their business plans. These outcomes were related to quality of service such as leakage and unplanned interruptions. However, GHG emissions were not part of financial incentives. It had only reputational impact on companies. In the 2024 price review, the regulator will link outcomes related to GHG with financial penalties and rewards. For this reason, our findings evidenced that carbon performance of water companies suffered a notable retardation during 2016–2020. On average, CE for WoCs dropped from 0.788 in 2016 to 0.690 in 2020. Average WaSC continued to report low levels of environmental efficiency reaching the level of 0.381 in 2020. Overall, the results indicate that both types of companies need to improve their managerial practices and adopt new technologies to control GHG emissions and improve environmental performance. Average WoC appeared to be the leaders in environmental efficiency however their performance reduced over time. At the same time less efficient WaSCs did not manage to catch-up with the frontier WoCs over time because GHG efficiency deteriorated as well.

4.3. Quantification of potential greenhouse gas savings

The estimation of the CE scores for each observation embracing the sample of this case study allowed us to quantify potential GHG savings by applying Eq. (6). Fig. 6 shows the annual estimated potential GHG savings for the English and Welsh water companies from 2011 to 2020. Total potential GHG savings for the 10 years evaluated were estimated to be 4,883,218 tons of CO_{2eq} which involves an annual average of 488,321 tons of CO_{2eq}. Nevertheless, Fig. 6 evidences that potential GHG savings were not constant across years but ranged between 407,558 tons of CO_{2eq}/year and 558,816 tons of CO_{2eq}/year. Variability in potential GHG savings across years is due to variations in the CE of water companies (Fig. 5), volume of drinking water supplied, and number of connected properties served.

Potential GHG savings per cubic meter of drinking water supplied also varied across years (Fig. 7). The average value for the 2011-20 period is 0.034 tons CO_{2eq}/m^3. This means that on average, the English and Welsh water companies could reduce 0.034 tons of CO_{2eq} for each cubic meter of drinking water supplied. The maximum value was reported in 2015 and corresponded to 0.039 tons CO_{2eq}/m^3 whereas the minimum value was 0.031 tons CO_{2eq}/m^3 for 2020. In general terms, Fig. 7 evidences that between 2011 and 2015, potential GHG savings per cubic meter of drinking water delivered increased over time and after 2015 a progressive reduction was achieved. A similar pattern is revealed when potential GHG savings were estimated per connected property

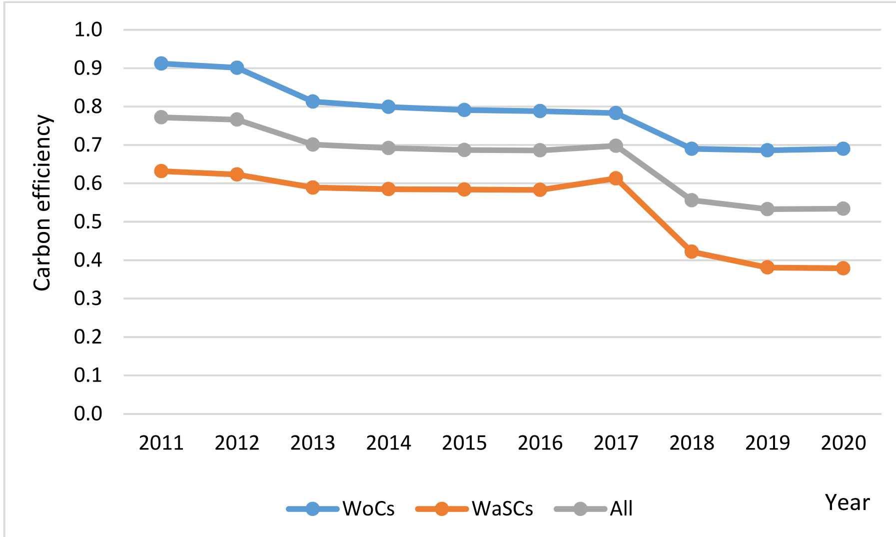

Fig. 5. Evolution across years of carbon efficiency scores for English and Welsh water companies.[11]

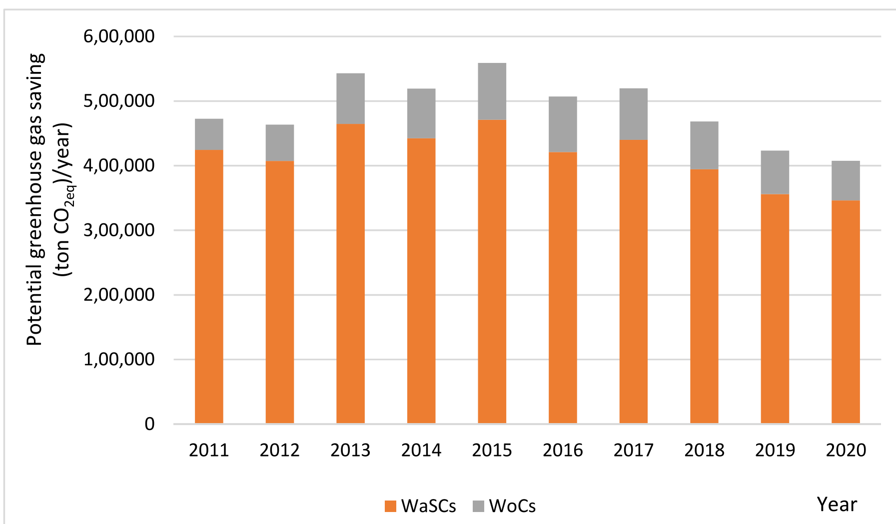

Fig. 6. Total annual potential greenhouse gas emissions savings for the English and Welsh water companies evaluated.

(Fig. 8). In this case, the average value for 2011-20 was 16.16 tons CO_{2eq}/connected property per year. This means that each year, water companies could save 16.16 tons of CO_{2eq} per connected property. The maximum value was observed in 2018 (18.38 tons CO_{2eq}/connected property per year) and the minimum in 2020 (14.21 tons CO_{2eq}/connected property per year). The dynamics of potential GHG emissions shown in Figs. 6–8 revealed that the English and Welsh water industry have begun to make efforts to improve its carbon footprint.

Because WaSCs provide drinking water services to a larger number of customers than WoCs (Ofwat), potential GHG savings of WaSCs are also larger than those for WoCs. On average, 85.3% of the total potential GHG savings of the English and Welsh water industry correspond to WaSCs (4,176,325 tons CO_{2eq} for 2011-20). By contrast, potential GHG savings for WoCs for the same period were estimated to be 715,893 tons CO_{2eq}. Focusing of potential GHG savings per cubic meter of drinking water supplied (Fig. 7) and per connected property (Fig. 8), it is revealed that WoCs performed better than WaSCs. On average, WoCs could save 0.025 tons CO_{2eq}/m^3 whereas for WaCs, potential savings were 0.040 tons CO_{2eq}/m^3. It suggests that potential GHG savings per cubic meter of drinking water delivered by WaSCs is 62.15% larger than for WoCs. Considering potential savings per connected property, WaSCs and WoCs could save, on average, 18.76 and 12.06 tons CO_{2eq}/connected property per year, respectively. It means that potential GHG savings of WaSCs are 55.55% larger than those for WoCs.

4.4. Operational characteristics influencing carbon efficiency of water companies

The final step in our analysis is to get a better understanding on the factors that impacted CE of water companies over time. In doing so, the regression analysis shown in Eq. (7) was applied. The results (see Table 3) indicate that all variables, but population density had a significant impact on companies' CE. It was found that average pumping head and the percentage of water taken from boreholes had a negative influence on CE. This means that higher pumping might be related to higher levels of energy use which could lead to higher levels of GHG emissions released to the atmosphere. This could result in lower levels of CE. Similarly, the more water is taken from boreholes, the higher the energy requirements could be which could have a negative impact on CE. In contrast, lower energy requirements might be needed to transport

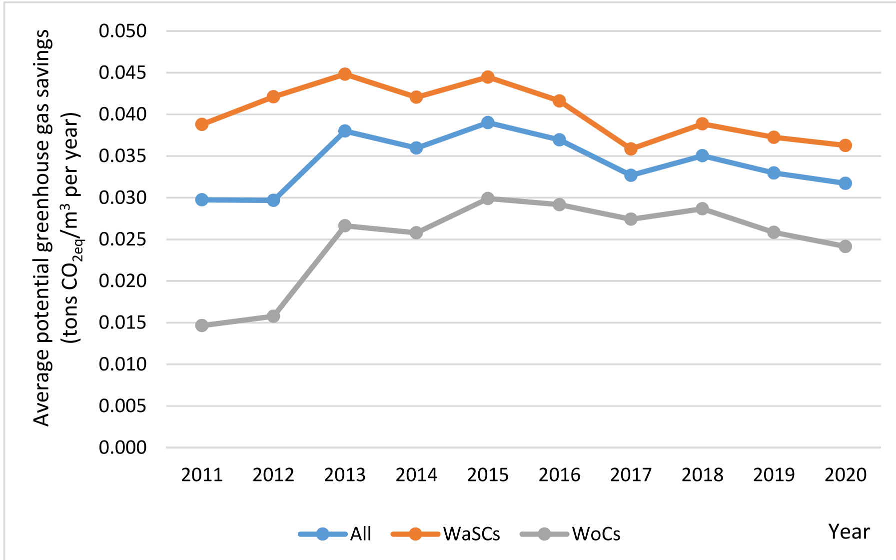

Fig. 7. Evolution of the average potential greenhouse gas emissions savings for the water companies evaluated per cubic meter of drinking water supplied.[21]

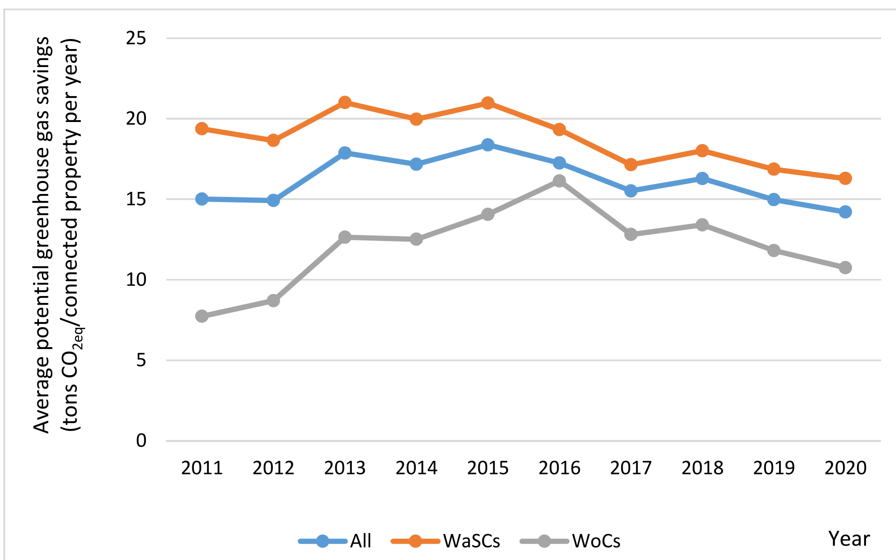

Fig. 8. Evolution of the average potential greenhouse gas emissions savings for the water companies evaluated per water connected property.[31]

water from reservoirs to treatment plants and thus, lower could be the impact on CE. In terms of raw water treatment, it was evidenced that the more complex the treatment of water, the higher the energy use could be which could result in higher levels of carbon inefficiency. Moreover, when water is taken from surface and groundwater resources and the more energy needs to be used to ensure that water is potable before it is distributed to end users. Consequently, the number of treatment works could be higher which might have a negative impact on CE. Finally, the time variable had a negative sign which means that on average CE reduced over time.

5. Discussion

The estimation of the optimal level of GHG emissions in the provision of drinking water (Fig. 3) evidenced that the size of the water companies, both in terms of water connected properties and volume of drinking water supplied, significantly influence the optimal level of GHG emissions. Hence, water regulators should not define fixed and equal GHG emissions' targets for all water companies. By contrast, the water regulator should be set more bespoke targets to improve the environmental performance of water companies. In this context, water companies can explore different approaches to achieve GHG emission targets defined by the water regulator. On the one hand, water companies can reduce energy consumption by adopting energy efficiency measures such as efficient pumps, leak detection sensors and other digitally-powered solutions. On the other hand, complementary measures involve the use of energy from renewable sources whose GHG emissions are lower. For example, it is possible to generate electricity from the hydraulic flow around the water distribution network.

CE estimations at water company level (Fig. 4) illustrate that both WaSCs and WoCs, present large variability in their carbon performance. In other words, there are water companies whose environmental performance in terms of GHG emissions is poor but there are also several

[1] Standard deviation values are shown in supplemental material.

Table 3
Influence of operational characteristics on carbon efficiency. Estimates of bootstrap truncated regression.

Variables	Coef.	Bootstrap Std. Err.	z-stat	p-value
Constant	8.413	1.901	**4.426**	0.000
Average pumping head	−0.170	0.095	***−1.790***	0.073
% water taken from boreholes	−0.570	0.171	**−3.323**	0.001
% water taken from reservoirs	0.383	0.154	**2.490**	0.013
Population density	−0.094	0.123	−0.763	0.445
Number of treatment works for surface water	−0.008	0.003	**−3.257**	0.001
Number of treatment works for groundwater	−0.004	0.001	**−4.345**	0.000
% water receiving high levels of treatment	−0.620	0.161	**−3.861**	0.000
Time	−0.041	0.009	**−4.401**	0.000
Sigma	0.232	0.022	**10.64**	0.000
X^2 (8)	**53.14**			
p-value	0.000			

Carbon efficiency is the dependent variable.
Bold indicates that coefficients are statistically significant at 5% significance level.
Bold italic indicates that coefficients are statistically significant at 10% significance level.

water companies which present large CE scores. This finding evidences that the current policies implemented by the water regulator have not been enough effective to achieve common standards for all water companies. By contrast, the carbon performance of water companies seems to be the result of individual efforts carried out by water companies to reduce their carbon footprint.

The United Kingdom (UK) has domestic targets for reducing GHG emissions under the Climate Chen et al., 2018 (CCA, 2018) . Moreover, the Nationally Determined Contribution (NDC) commits the UK to reducing economy-wide GHG emissions by at least 68% by 2030, compared to 1990 levels (NDC UK, 2022). Estimated potential GHG savings in this study (Fig. 6) represent a very small fraction of total GHG emissions to be reduced in UK. However, from a policy perspective is essential that all sectors and industries contribute to achieve the UK commitments in terms of GHG reductions. According to the Department of Business, Energy & Industrial Strategy (2022), the UK had GHG emissions of around 7 tons of CO_{2eq} per person in 2019. Considering that potential GHG savings in the provision of drinking water services were around 407,558 tons of CO_{2eq} per year, they represent the GHG annually emitted by 58,223 people which is equivalent to cities such as Chelsea or Canterbury (UK population data, 2022).

The operational variables influencing the CE of water companies (Table 3) are mainly related to the source of raw water and its quality. Thus, measures at watershed scale should be implemented to improve water quality minimizing energy consumption to produce drinking water and therefore, reducing GHG emissions by water companies. It should be noted that several stakeholders and water users (public and private) are involved in the management of watersheds and therefore, cooperation and collaboration among them is fundamental for decision-making and effectively implement the defined actions.

6. Conclusions

Within the current climatic emergency framework, evaluating CE of water utilities is a useful tool to better understanding water-energy nexus. Whereas different methodological approaches can be applied to estimate CE, the only one that overcomes overfitting issues and allows estimating optimal levels of GHG emissions is the EAT approach. Thus, this method was used to evaluate CE scores, optimal levels of GHG emissions and potential GHG savings for a sample of English and Welsh water companies in the provision of drinking water.

Results have revealed that the optimal level of carbon emissions of water companies depends on the volume of drinking water supplied and the number of connected properties. Thus, bespoke targets for each water company should be set by the water regulator to reduce GHG emissions. Carbon performance of the water companies evaluated was moderate as the average CE for the 160 observations analyzed was at the level of 0.632 which means that GHG emissions could go down by 36.8% to maintain the same level of water services. Moreover, CE followed a downward trend over time which means that water companies in England and Wales need to make substantial efforts to improve performance. Average potential GHG savings were estimated to be 0.034 tons of CO_{2eq}/m^3 and 16.16 tons of CO_{2eq}/connected property per year. Relevant differences were observed between WaSCs and WoCs because average potential GHG savings were 0.040 tons of CO_{2eq}/m^3 for WaSCs and 0.025 tons of CO_{2eq}/m^3 for WoCs. The bootstrap regression results revealed that topography and water treatment complexity had a significant impact on CE of water companies.

The estimation of CE scores and the quantification of the potential GHG savings allows regulated managers to better understand the water-energy nexus within the urban water cycle. The path toward a net zero carbon water industry requires a good understanding of how well is performing in terms of reducing GHG emissions and what drives carbon performance. Based on the low carbon performance of the English and Welsh water industry, the water regulator should adopt additional policies to promote the reduction of GHG emissions by water companies. For example, penalties and rewards could be established by the water regular in the process of setting water tariffs based on two main criteria: i) quantity of GHG emissions per cubic meter of drinking water supplied and; ii) percentage of reduction of GHG emissions in relation to previous regulatory periods. Reducing carbon footprint in the provision of drinking water requires retrofitting existing systems to more energy efficient ones. Those investments should be considered by the water regulator when setting water tariffs. Moreover, citizens can also play a relevant role by reducing drinking water demand. Other policy-makers such as city planners might also contribute to reduce the carbon footprint in the provision of drinking water by designing water-wise cities which consider the links between water companies, water users and watershed management.

Although this study provides a useful method so that water utilities meet their environmental challenges, it is not exempt of limitations. The assessment conducted in this study focused on the drinking water services, and therefore, further research including wastewater collection and treatment could be pursued in future. The outputs considered in this study did not take into account either raw water quality or drinking water quality. Therefore, CE divergences among water companies could be due to differences in the concentration of pollutants to be removed to produce drinking water. Moreover, only a single production frontier integrating data from 2011 to 2020 was estimated and therefore, the evolution of CE scores should be interpreted with caution. Thus, future research on this topic might evaluate the dynamics of CE, i.e., carbon productivity change of water companies by estimating shifts of the production frontier over time and also movements of the units in relation to yearly estimated production frontiers. It should be also interesting to compare the CE of English and Water companies with utilities operating under different regulatory context to get a better understanding on the impact of regulation on the carbon performance of water companies.

CRediT authorship contribution statement

Alexandros Maziotis: Methodology, Sofware, Writing – original draft. **Ramon Sala-Garrido:** Data curation, Writing – review & editing. **Manuel Mocholi-Arce:** Writing – review & editing, Supervision. **Maria**

[3] Standard deviation values are shown in supplemental material.
[3] Standard deviation values are shown in supplemental material.

Molinos-Senante: Conceptualization, Visualization, Writing – review & editing.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136304.

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