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Accounting for Heterogeneity in the Water-Energy-Carbon Nexus: Evidence from English and Welsh Water Utilities

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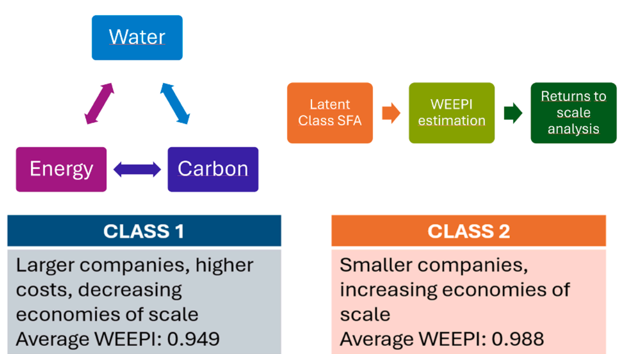
HIGHLIGHTS

- A water-energy-emissions performance index was estimated for water companies
- The performance index integrates utility-specific heterogeneity.
- Regulatory frameworks should be target specific for companies´ classes

GRAPHICAL ABSTRACT



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ABSTRACT

Improving energy and carbon efficiency in the provision of water services is essential towards more sustainable urban water cycle. This study investigates the performance of water companies in England and Wales by explicitly incorporating heterogeneity into the evaluation of the water-energy-carbon nexus. A novel Water-Energy-Emissions Performance Index (WEEPI) is developed using a latent class stochastic frontier analysis (SFA) framework, accounting for unobserved differences in production technologies across utilities. The analysis, based on data from 2011 to 2019, reveals two distinct classes of water companies. Class 1 companies generally demonstrate slightly higher WEEPI scores than Class 2 companies with average WEEPI of 0.949 and 0.938, respectively. The study finds that economies of scale are prevalent in Class 2 companies, suggesting strategic growth opportunities, while Class 1 companies face diminishing returns. Moreover, environmental factors such as average pumping head and treatment complexity exert class-specific impacts on efficiency. These findings underscore the importance of tailoring regulatory frameworks and incentives to company-level heterogeneity, thereby supporting more equitable and effective transitions towards carbon-neutral and energy-efficient water services.

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1. Introduction

The intricate interconnections among energy, carbon, and water—commonly referred to as the water-energy-carbon nexus—have been widely acknowledged (Li et al., 2025; Xie et al., 2024; Yu et al., 2020). The United Nations' Sustainable Development Goals (SDGs) underscore the importance of considering these three elements as interconnected components in the pursuit of sustainable development by 2030. Specifically, the SDGs emphasize the need to improve energy efficiency and adopt renewable energy sources (Goal 7), reduce greenhouse gas (GHG) emissions to combat climate change (Goal 13), and ensure the availability and sustainable management of water and sanitation services for all (Goal 6) (United Nations, 2015). However, recent global trends suggest progress is not moving in the desired direction. In 2024, global energy demand grew by 2.2%, outpacing the annual average growth rate of 1.3% observed between 2013 and 2023 (IEA, 2025). Moreover, global GHG emissions rose by 9% from 2010 to 2022 achieving 53,851 million tonnes per year (Jones et al., 2023). Regarding water consumption, global demand for freshwater has steadily increased by just under 1% per year since the 1980s (UNESCO, 2025a).

Focusing on the provision of drinking water services, energy consumption accounts for between 10% and 30% of the total annual costs incurred by water companies (Maziotis et al., 2024a). However, there is significant variability across utilities, with energy use ranging from 0.44 kWh/m^3 to 1.82 kWh/m^3 depending on factors such as facility size, raw water quality and source, and management practices (WAREG, 2023). In terms of GHG emissions, the urban water sector is estimated to contribute between 1% and 3% of national total carbon emissions (Zhang et al., 2024). These figures highlight the urgent need for a paradigm shift in drinking water provision towards more sustainable and efficient practices (Walker et al., 2021). Encouragingly, several initiatives are underway to support the water sector's transition to net-zero carbon emissions. For instance, the United Kingdom government has set a target to achieve net-zero carbon emissions for the water companies by 2030 (CCC, 2019), while the United Nations' Race to Zero initiative also incorporates the drinking water sector (UNESCO, 2025b).

From a scientific perspective, several studies have aimed to deepen the understanding of the water-energy-carbon nexus in water service provision by assessing the performance of water companies using a synthetic index that integrates three key components: energy consumption, GHG emissions, and drinking water delivery (Ananda, 2018; Walker, 2019; Mocholi et al., 2024; Tian et al., 2025). This synthetic index has been typically estimated using multi-criteria methods within the framework of production theory, based on the fundamental assumption that water companies require energy to deliver drinking water, and their operations inevitably produce GHG emissions (Vilarinho et al., 2023; Flegl et al., 2024). Such a methodological approach allows for the benchmarking of performance across the sample of water companies, facilitating meaningful comparisons and identifying best practices.

Focusing on the specific multi-criteria methods employed to assess the water-energy-carbon nexus within the water sector, two main approaches can be distinguished. Most studies have utilized Data Envelopment Analysis (DEA), a non-parametric method that does not require the specification of a functional form for the production frontier. However, DEA's deterministic nature involves it does not incorporate noise or account for environmental variables, attributing any deviation from the efficient frontier solely to inefficiency (Lamb and Tee, 2024). In this context, Ananda and Hampf (2015) and Ananda (2018) assessed the impact of GHG emissions on the performance of Australian water companies. Meanwhile, a substantial body of work has focused on water companies in England and Wales, driven by the legal commitment to achieve carbon neutrality by 2030 (Sala-Garrido, 2021, 2023; Maziotis et al., 2024a). Conversely, some studies also focused on the English and Welsh water sector have employed Stochastic Frontier Analysis (SFA) as a multi-criteria method (Molinos-Senante and Maziotis, 2022; Molinos-Senante et al., 2022). As a parametric approach, SFA requires defining the functional form of the production frontier a priori, but it offers the advantage of distinguishing between random noise and inefficiency.

Regardless of whether DEA or SFA is used to assess the performance of water companies by integrating energy, carbon, and water variables, most previous studies have assumed that the assessed water companies are homogeneous. However, this assumption is critical, as efficiency results are highly sensitive to this foundational premise (Ananda and Oh, 2023). In practice, heterogeneity among water companies can stem from differences in size, geographic location, and ownership structure (De Witte & Marques, 2009; Lozano and Borrego-Marin, 2025). To address this limitation, Molinos-Senante and Maziotis (2025) estimated carbon efficiency for English and Welsh water companies using the metafrontier approach, distinguishing between water and sewerage companies and water-only companies. However, this approach requires prior knowledge of the key variables that drive heterogeneity among water companies. However, heterogeneity may arise from multiple, overlapping factors, further complicating the classification process. If heterogeneity is not fully observable at the outset, the metafrontier approach may not be applicable and can lead to biased efficiency estimates (Dakpo et al., 2024).

To address the aforementioned limitation and improve the understanding of the water-energy-carbon nexus in the provision of drinking water, this study proposes and estimates a synthetic index—the Water-Energy-Emissions Performance Index (WEEPI)—which explicitly accounts for heterogeneity among water companies. By incorporating potential unobserved differences, the WEEPI enables a more holistic evaluation of performance, ensuring that benchmarking results are more reliable by comparing truly comparable (homogeneous) water companies. Furthermore, the insights gained from this performance assessment are particularly valuable for policymakers, as they support the development of tailored policies and measures suited to the specific characteristics of each class of water companies.

The main novelty of this study is the development and application of the WEEPI, a synthetic index that explicitly considers heterogeneity among water companies when evaluating performance. While previous studies have used metafrontier approaches to account for observable heterogeneity—typically by pre-classifying companies based on factors like size or service type —such methods rely heavily on a priori groupings, which may overlook more nuanced or unobserved differences. In contrast, the latent class SFA approach adopted in this study allows for endogenous classification based on companies' observed behavior and performance profiles. This is particularly relevant in the context of the water-energy-carbon nexus, where heterogeneity may arise from overlapping technological, environmental, and organizational factors that are not easily captured by simple categorical variables. This methodological innovation builds upon and extends earlier efficiency studies of English and Welsh water utilities, which have typically assumed homogeneous technologies and ignored class-specific performance structures. By employing a latent class SFA framework, the WEEPI integrates energy consumption, GHG emissions, and water delivered, enabling a more accurate and nuanced benchmarking of performance. Moreover, in contrast to Ofwat's existing benchmarking, which relies on partial indicators or deterministic cost comparisons, WEEPI offers a probabilistically grounded, multivariate metric suitable for regulatory and policy use.

Within the urban water sector, the application of latent class SFA models for performance evaluation remains scarce. To the best of the authors' knowledge, Sala-Garrido et al. (2025) is the only study to date that applies this methodology to classify and assess both carbon and pollutant efficiency in Spanish wastewater treatment plants. Additionally, Maziotis and Molinos-Senante (2025) used latent class SFA to compare the technical efficiency of Chilean water utilities, although their analysis focused solely on water production and cost, without incorporating carbon emissions. These few applications highlight the untapped potential of latent class models for capturing unobserved heterogeneity in water utility performance, especially in relation to environmental dimensions.

Beyond the water sector, latent class SFA has seen broader application in other utility contexts. For instance, in the energy sector, Orea and Jamasb (2017) employed it to benchmark the performance of Norwegian electricity distribution networks, while Cullmann et al. (2012) used the approach to analyze German electricity distribution companies. These studies demonstrate the method's value in addressing heterogeneity across utility firms and improving the robustness of performance estimates. The agricultural sector, particularly dairy farming, has shown the greatest uptake of latent class SFA, with recent applications by Latruffe et al. (2023), Garcia-Covarrubias et al. (2023), and Stetter et al. (2023) aimed at benchmarking farm performance under diverse operational conditions. Overall, while latent class SFA is increasingly recognized for its ability to account for unobserved heterogeneity, its use in the water sector—especially for analyzing the water-energy-carbon nexus—remains very limited.

2. Methodology

To estimate the WEEPI for each water company while accounting for potential heterogeneity in production technologies, we employed the latent class SFA approach proposed by Orea and Kumbhakar (2004). This methodology allows all model parameters to vary across latent classes, capturing differences in technologies, operating environments, and management practices among groups of companies (Cullmann, 2012). A key strength of this approach lies in its ability to classify firms endogenously—based solely on company-specific data such as inputs, outputs, and environmental conditions—without requiring any a priori assumptions about group membership. This represents a significant advancement over conventional metafrontier approaches, which require firms to be exogenously grouped based on predefined criteria (e.g., size, ownership, region, or technology type). Such classifications can be arbitrary or subjective, potentially masking unobserved heterogeneity. In contrast, the latent class SFA model uncovers group structures directly from the data, leading to a more data-driven and flexible benchmarking process. Moreover, it simultaneously separates inefficiency from statistical noise, providing more accurate and reliable efficiency estimates. By leveraging this methodological advantage, our study offers a novel contribution to the water utility literature, particularly in the context of integrating environmental and energy-related performance metrics through the WEEPI framework. Unlike deterministic approaches such as DEA, which attribute all deviations from the frontier to inefficiency, SFA decomposes the error term into two components: (i) a symmetric noise term, capturing random shocks and measurement errors, and (ii) a one-sided inefficiency term, representing technical inefficiency. This distinction is crucial given the potential influence of exogenous changes (e.g., energy price volatility) in the water sector.

In this case study, four main stages were subsequently applied as it is shown in Figure 1:

Let us assume that there are K total water companies in the sample, which can be divided into j sub-groups or classes based on their production technology. For each class j, the production technology is defined as follows:

$$PT_j = \left\{ (x, y)|_j : x \text{ can generate } y|_j \right\} \tag{1}$$

where x denotes the vector of variables to be minimized, i.e., inputs employed to generate a vector of outputs or variables to be maximized, y, based on j production technology. This technology can be represented with the use of distance functions.

In this study, the objective for improving the WEEPI is to enable water companies to maintain the provision of water to customers while minimizing energy use and GHG emissions. Consequently, water companies aim to minimize their use of inputs, which is captured through the input distance function. Carbon emissions were incorporated as an input to be minimized, consistent with prior studies that treat emissions as a direct consequence of production processes requiring minimization (Li et al., 2022; Rodríguez & Trujillo, 2025; Shimizu & Tiku, 2023). In this framework, the WEEPI reflects the joint minimization of energy use, labor costs, and GHG emissions while maximizing water delivered. Considering carbon emissions as a dependent output would risk underestimating their intrinsic role as a controllable performance factor, as water companies can directly implement strategies (e.g., renewable energy adoption, treatment optimization) to reduce them (Sala-Garrido et al., 2023).

The input distance function represents the maximum proportion (ρ) by which inputs can be contracted without any reduction in outputs (Zhu et al., 2025). For each class j the input distance function is defined as follows:

$$D_I|_j(x, y) = sup\{\rho : \ (x/\rho, y) \in PT_j\}, \ j = 1, \ldots, J \tag{2}$$

The input distance function can be modeled using various functional forms, including translog, Cobb-Douglas, quadratic, or generalized Leontief (Win et al., 2021). While each form has its own advantages and disadvantages, this study employed the translog functional form to specify the input distance function. The translog functional form was selected due to its greater flexibility and ability to capture complex production relationships (Sarker et al., 2022). Unlike Cobb–Douglas, which imposes constant elasticities and unitary substitution between inputs, the translog form allows for variable elasticities of substitution, second-order interactions between inputs, and non-constant returns to scale. These characteristics are essential in modeling the performance of English and Welsh water companies that operate under diverse environmental, technological, and organizational conditions (Saal et al., 2007).

For each class j the input distance function can be estimated using the translog form as follows:

$$\begin{aligned} -\ln x_{Mit}|_j \ &= \alpha_{0j} + \sum_{M=1}^{M-1} \beta_{mj} \ln \widetilde{x}_{mit} + \frac{1}{2} \\ &\sum_{m=1}^{M-1} \sum_{l=1}^{M-1} \beta_{mlj} ln \widetilde{x}_{mit} \ln \widetilde{x}_{lit} + \sum_{n=1}^{N} {}_{nj} \ln y_{nit} + \frac{1}{2} \sum_{n=1}^{N} \sum_{p=1}^{N} {}_{npj} ln y_{nit} \ln y_{pit} \\ &+ \sum_{m=1}^{M-1} \sum_{n=1}^{N} \gamma_{mnj} \ln \widetilde{x}_{mit} ln y_{nit} + \sum_{n=1}^{N} \delta_{nj} \ln y_{nit} t + \sum_{m=1}^{M-1} \eta_{mj} \ \ln \widetilde{x}_{mit} t \\ &+ \varphi_1 t + \frac{1}{2} \varphi_2 t^2 + \sum_{q=1}^{Q} \zeta_{qj} z_{qit} + v_{ijt} \ - \ u_{ijt} \end{aligned} \tag{3}$$

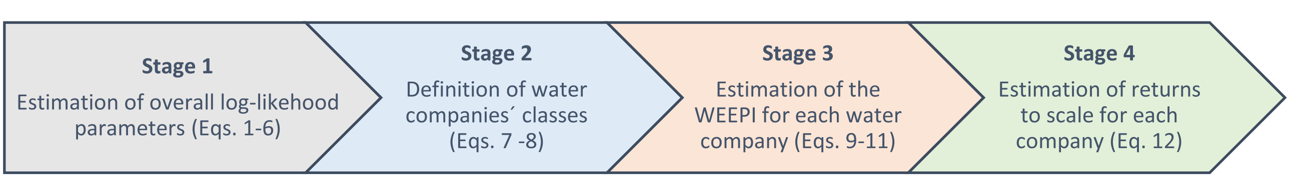

Figure 1. Methodological stages of the study.

where M and N are the total number of variables to be minimized and maximized, respectively; i is the number of water companies in the sample, t denotes time, a_0 is the constant term for each class j, v_{ijt} is the noise term of each water company for each class over time and u_{ijt} is the WEEPI of each water company i for each class over time. In Eq. (3) $\widetilde{x_m} = \frac{x_m}{x_M}$ due to the imposition of homogeneity of degree 1 in inputs.

The error structure in Eq. (3) is composed, $\varepsilon_i = v_i - u_i$, where the noise term $v_i \sim \mathcal{N}(0, \sigma_v^2)$ and the non-negative inefficiency term $u_i \sim half \sim \mathcal{N}(0, \sigma_u^2)$ are independently distributed.

The latent class SFA model used in this study, allows both the production frontier parameters and the distributional parameters (σ_v, σ_u) to vary across classes. This specification captures heterogeneity not only in technology, but also in the stochastic structure of the composed error term — reflecting the possibility that utilities in different classes face distinct noise environments and inefficiency profiles.

The log likelihood for each class j is defined as follows (Alvarez and de Corral, 2010; Alvarez et al., 2012):

$$LF_{itj} = f(y_{it}|x_{it}, \beta_j, \sigma_j, \lambda_j) = \frac{\Phi\left(\lambda_j \cdot \varepsilon_{it}|_j / \sigma_j\right)}{\Phi(0)} \cdot \frac{1}{\sigma_j} \cdot \varphi\left(\frac{\varepsilon_{it}|_j}{\sigma_j}\right) \tag{4}$$

where $\sigma_j = \left(\sigma_{uj}^2 + \sigma_{vj}^2\right)^{\frac{1}{2}}$; $\lambda_j = \frac{\sigma_{uj}}{\sigma_{vj}}$; Φ is the cumulative distribution function and; φ is the standard normal density (Alvarez et al., 2012).

The log-likelihood of each water company i is derived by employing the prior probabilities of class j membership as weights (Lin and Du, 2014):

$$LF_i = \sum_{j=1}^{J} P_{ij} LF_{ij},\ 0 \le P_{ij} \le 1,\ \sum_j P_{ij} = 1 \tag{5}$$

According to Barros et al. (2011), the overall log-likelihood is defined as follows:

$$logLF = \sum_{i=1}^{K} logLF_i \tag{6}$$

The optimal number of classes j is determined by carrying out a likelihood ratio test between the model with j classes and the model with $j-1$ classes (Greene, 2007). Moreover, to provide a more robust approach, the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBIC) were applied (Orea and Kumbhakar, 2004; Barros, 2011). They are defined as follows:

$$AIC = -2logLF(j) + 2\theta \tag{7}$$

$$SBIC = -2logLF(j) + log(K)^*\theta \tag{8}$$

where $logLF(j)$ represents the value of the log-likelihood function for j class, θ denotes the number of estimated parameters, and K is the number of observations. The optimal model for determining the number of classes in the sample of water companies is the one with the lowest AIC and SBIC (Cullmann and Zloczysti, 2014).

After estimating the parameters of the overall log-likelihood (Eq. 6), the WEEPI of each water company i for each class j is estimated as follows (Lin and Du, 2014):

$$WEEPI_{it|j} = \exp(-u_{it|j})|\varepsilon_{it|j} \tag{9}$$

As Greene (2005) noted, the probabilities of class membership can be obtained through Bayesian theorem after estimating the parameters of the log-likelihood function (Alvarez et al., 2012; Lin and Du, 2014).

$$P(j|i) = \frac{P_{ij} LF_{ij}}{\sum_{j=1}^{J} P_{ij} LF_{ij}} \tag{10}$$

Subsequently, the WEEPI of each water company i for each class j at any time t based on posterior information is estimated as follows (Lin and Du, 2014):

$$WEEPI_{it} = \sum_{i=1}^{J} \left(P(i|j) \times WEEPI_{it|j}\right) \tag{11}$$

Finally, to better understand potential factors—such as economies of scale—driving differences in WEEPI scores among classes, the returns to scale (RTS) for each water company i in class j at time t were estimated as follows:

$$RTS_{it|j} = -\frac{1}{\vartheta lnx_{Mit|j} / \vartheta lny_{it|j}} \tag{12}$$

A $RTS_{it|j}$ value greater than 1 indicates increasing economies of scale, meaning that output (water delivered) increases by more than the proportional increase in inputs (energy costs and GHG emissions). Conversely, a $RTS_{it|j}$ value less than 1 suggests decreasing economies of scale, reflecting the opposite pattern between inputs and outputs. Finally, a $RTS_{it|j}$ value equal to 1 denotes constant returns to scale implying that inputs and ouputs change in the same proportion.

3. Case study description

The methodological framework for estimating WEEPI was applied to a sample of English and Welsh water companies during the period 2011-2019. The analysis is based on data from 2011 to 2019, reflecting the most recent period for which complete, consistent, and regulator-validated information is available across all variables. Post-2019 data were excluded to avoid the atypical effects of the COVID-19 pandemic, which significantly disrupted operational conditions and demand patterns in the water sector (Vizanko et al., 2024; Walker et al., 2023). Including these years could compromise the robustness and comparability of efficiency estimates. Future research should revisit the analysis once stabilized post-pandemic datasets become available. The total number of observations assessed was 164. As private entities, these companies are regulated by the Water Services Regulation Authority (Ofwat), which operates under a price (revenue) cap system. Every five years, Ofwat determines the companies' allowed revenue, while also monitoring their economic and environmental performance to ensure that customers receive the best possible service at the most affordable cost (Ofwat, 2022).

The selection of variables in this analysis was based on previous studies, the main objective of the study and data availability (Pinto et al., 2017; Cetrulo et al., 2019; Goh and See, 2021). The defined variables to be minimized included: i) energy costs associated with the provision of water services, measured in millions of pounds per year; ii) labor costs (salaries), also measured in millions of pounds per year; and iii) GHG emissions, expressed in tonnes of CO_2 equivalent (CO_{2e}) per year. These emissions involve Scope 1 emissions, Scope 2 emissions and some Scope 3 emissions related to the purchased of goods and services as well as contracted waste. GHG emissions are measured according to the UK Government Environmental Reporting Guidelines (HM Government, 2019). On the other hand, the variable to be maximized was the annual volume of water delivered, measured in thousands of cubic metres.

Given the evidence in the literature that environmental variables can significantly influence the performance of water companies, this assessment incorporated several variables identified in previous studies focusing on English and Welsh water utilities (Walker et al., 2020; Maziotis et al., 2024b). To capture the influence of raw water sources, the percentage of water abstracted from surface water sources was included. To account for the energy requirements associated with transporting raw water over varying topographies, the average pumping head was considered. Additional environmental variables were linked to the quality of raw water, which in turn affects the complexity of water treatment processes. More advanced treatment levels typically lead to higher energy costs, increased carbon emissions, and thus, lower efficiency (Sala-Garrido et al., 2021). The variables reflecting treatment complexity included the percentage of surface water treatment works, the percentage of groundwater treatment works, and the percentage of water undergoing advanced-level treatment (for detailed definitions, see Ofwat, 2018). Finally, population density, defined as the ratio of population to area, was also incorporated into the assessment.

Table 1 presents the descriptive statistics for all variables included in the analysis, with data sourced from the annual reports of Ofwat.

While the latent class SFA framework endogenously identifies groups of companies with distinct production technologies, theory and empirical evidence suggest several structural factors that may also drive heterogeneity among utilities. These include: i) asset age and infrastructure condition, as older networks may entail higher leakage rates, energy use, and maintenance costs (Walker et al., 2020); ii) regional regulatory or policy environments, where local environmental policies and carbon reduction strategies can influence operational practices (Ma et al., 2024) and; iii) the adoption of renewable energy and green technologies, which directly affects the carbon intensity of operations (Aliani et al., 2024). Unfortunately, comprehensive data for these variables was not consistently available across all companies and years in our sample. Nonetheless, their role as potential determinants of heterogeneity should be recognized in future research.

4. Results and discussion

4.1. Estimation of the production frontier

Based on the proposed methodology, the AIC and the BSIC were estimated to determine the optimal number of classes for water companies, thereby addressing heterogeneity in the estimation of the WEEPI. For the two-class model, the AIC and BSIC were -407.9 and -397.6, respectively, whereas for the single-class model, these values were -286.7 and -281.8. Consequently, the data supported the existence of two distinct classes of water companies in the sample. Furthermore, a likelihood ratio test (LR=171.66) rejected the single-class model. The estimated prior probabilities indicated that 32.5% of the observations were allocated to class 1, with the remaining observations assigned to class 2. Although a three-class specification was initially considered, the model failed to converge despite extensive efforts using various estimation strategies. Specifically, the log-likelihood function did not reach a stable maximum, even after increasing the maximum number of iterations, adjusting the convergence tolerance criteria, and applying multiple sets of starting values (both random and fixed). Diagnostic checks revealed that the third latent class led to near-singular covariance structures and unstable parameter estimates, particularly for the interaction terms and second-order variables. This suggested a lack of sufficient statistical separation between groups or an insufficient number of observations to support reliable estimation for all three classes. Additionally, the posterior class membership probabilities indicated that the third class consistently received negligible weight across multiple runs, further suggesting that it lacked empirical support in the data. Attempts to impose parameter constraints to aid convergence (e.g., simplifying interaction terms or reducing functional complexity) did not resolve the instability. Based on these findings, and following best practices in latent class modeling, we retained the two-class model, which demonstrated robust convergence, clear empirical differentiation, and consistent parameter estimates across multiple initializations.

Table 1
Descriptive variables for assessing WEEPI for English and Welsh water companies over the period 2011-2019.

Variables	Unit of measurement	Mean	Std. Dev.	Minimum	Maximum
Energy costs	£m /year	18.64	15.03	0.53	60.53
Labour costs	£m /year	20.94	17.77	0.67	107.47
GHG	Ton CO_{2e} / year	77068	68709	3523	275900
Water delivered	000s m^3/year	243788	204329	8924	791616
Water taken from rivers	%	27.3	25.1	0.0	86.2
Surface water treatment works	%	34.5	130.2	2.9	87.3
Groundwater treatment works	%	67.2	510.2	4.1	92.3
Water receiving high levels of treatment	%	58.2	23.4	22.0	99.1
Average pumping head	meters	139	37	65	224
Population density	000s/km^2	0.47	0.28	0.15	1.25

Table 2 presents the main statistical characteristics of both water companies' classes. On the one hand, class 1 embraces large-sized companies characterized by higher costs, reflecting the substantial volumes of water they abstract, treat, and distribute. These companies also report elevated levels of GHG emissions and tend to serve areas with higher customer density. On the other hand, class 2 embraces small-sized companies requiring a greater number of treatments works, particularly when sourcing water from surface resources.

It is important to acknowledge that the classification of water companies into two latent classes may partly reflect omitted factors such as infrastructure age, renewable energy adoption rates, or region-specific policy interventions. However, robustness checks—comparing parameter stability across sub-periods and testing alternative specifications with available proxies —confirmed that the two-class model remains stable.

The econometric results obtained from the estimation of the latent class frontier model are presented in Table 3. The coefficients of the estimated parameters were normalized around the mean prior to estimation to allow their interpretation as elasticities. The estimated coefficients generally exhibit the expected signs and are statistically significant. However, differences in their magnitudes highlight the importance of estimating firms under different production frontiers to account for their heterogeneity.

For water companies embracing class 1, holding other variables constant, a 1% increase in the volume of water delivered is associated with an average 1.123% increase in energy costs, suggesting that these companies operate under decreasing economies of scale. By contrast, for water companies in class 2, a 1% increase in the volume of water delivered leads to a smaller average increase in energy costs of 0.746%, indicating small increasing economies of scale. A 1% increase in carbon emissions and labour costs results in energy cost increases of 0.158% and 0.254%, respectively, on average for class 1 companies while

Table 2
Average values of the two classes of water companies over the period 2011-2019.

Variables	Units	Class 1	Class 2
Water delivered	m^3/year	272040404	229259570
Energy cost	m£/year	22	17
Labour cost	m£/year	21	21
GHG	Ton CO_{2e}/ year	85745	72448
Population density	000s/km^2	0.554	0.420
% of water taken from river	%	20.6	30.7
Average pumping head	nr	131.574	142.949
Number of surface water treatment works	nr	9.069	18.451
Number of groundwater treatment works	nr	0.949	0.935
High levels of water treatment	%	61.3	56.5

Table 3
Estimates of SFA latent class model for class 1 and class 2 water companies (2011-2019).

Variables	Class 1				Class 2			
	Coeff.	St.Err.	T-stat	P-value	Coeff.	St.Err.	T-stat	P-value
Constant	-0.112	0.800	-0.140	0.889	3.801	0.209	**18.186**	0.000
Water delivered	-1.123	0.047	**-23.951**	0.000	-0.746	0.033	**-22.335**	0.000
GHG	0.158	0.048	**3.315**	0.001	0.211	0.030	**7.074**	0.000
Labour cost	0.254	0.056	**4.509**	0.000	0.227	0.020	**11.220**	0.000
Time	-0.025	0.004	**-5.649**	0.000	-0.030	0.003	**-9.142**	0.000
GHG^2	0.257	0.051	**5.073**	0.000	0.535	0.081	**6.603**	0.000
$Labour\ cost^2$	-0.479	0.148	**-3.245**	0.001	0.393	0.061	**6.444**	0.000
GHG*Labour cost	-0.016	0.070	-0.233	0.816	-0.166	0.066	**-2.503**	0.012
Water delivered*GHG	-0.048	0.024	**-1.982**	0.048	-0.018	0.020	-0.866	0.386
Water delivered*Labour cost	-0.111	0.030	**-3.666**	0.000	0.104	0.026	**3.958**	0.000
$Water\ delivered^2$	0.376	0.131	**2.874**	0.004	0.180	0.018	**10.161**	0.000
GHG *Time	0.027	0.004	**6.282**	0.000	0.070	0.016	**4.441**	0.000
Labour cost*Time	-0.033	0.012	**-2.798**	0.005	-0.044	0.012	**-3.680**	0.001
Water delivered*Time	0.009	0.003	**3.297**	0.001	-0.018	0.005	**-3.474**	0.000
$Time^2$	0.001	0.004	0.266	0.790	0.024	0.002	**10.398**	0.000
Number of groundwater treatment works	0.002	0.001	**2.093**	0.036	-0.002	0.000	**-3.853**	0.000
High levels of water treatment	0.360	0.499	0.721	0.471	-0.434	0.132	**-3.291**	0.000
Number of surface treatment works	0.005	0.003	1.544	0.123	-0.007	0.001	**-9.381**	0.000
Water taken from rivers	-0.053	0.085	-0.620	0.535	-0.045	0.022	**-2.011**	0.044
Average pumping head	-0.372	0.127	**-2.919**	0.004	-0.594	0.034	**-17.627**	0.000
Population density	0.195	0.043	**4.556**	0.000	-0.055	0.009	**-5.771**	0.000
Sigma	0.085	0.008	**10.549**	0.000	0.091	0.006	**14.502**	0.000
Lambda	21.377	10.319	**2.072**	0.038	19.730	8.997	**2.193**	0.028

Bold indicates that coefficients are statistically significant at 5% significance level; Bold italic indicates that coefficients are statistically significant at 10% significance level.

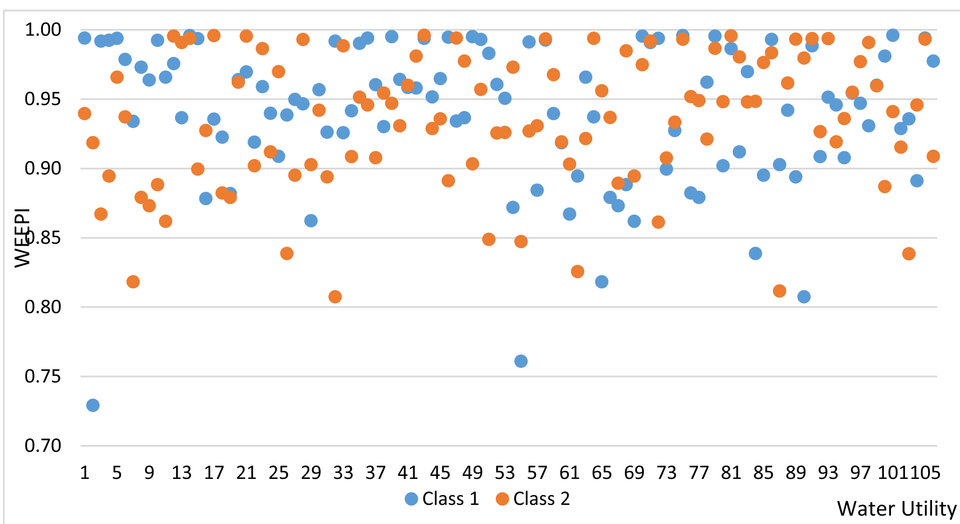

Figure 2. Water-Energy-Emissions Performance Index (WEEPI) for water companies embracing class 1 and class 2 over 2011-2019[1].

increases of 0.211% and 0.227%, respectively for class 2 companies. Technical regress was observed for both classes being estimated at 2.5% per year for class 1 and 3.0% for class 2. The interaction between the volume of water delivered and carbon emissions is statistically significant for water companies within class 1, with a 1% reduction in both variables leading to a 0.048% decrease in energy costs. For class 2, the interaction between volumes of water delivered and carbon emissions was not statistically significant.

The analysis of environmental variables' impact on efficiency revealed significant differences between class 1 and class 2 water companies. For class 1 companies, only three environmental variables had a significant influence: average pumping head, the number of groundwater treatment works, and population density. Higher average pumping head and more groundwater treatment works could lead to higher energy costs and inefficiency. By contrast, higher population density reduced energy costs, indicating economies of density in densely populated areas. On the other hand, class 2 companies experienced significant impacts from all environmental variables considered. Average pumping head and treatment complexity were particularly important. Increases in water abstraction from rivers, average pumping head, and advanced treatment levels consistently raised energy costs and inefficiency. Unlike class 1, class 2 companies exhibited slight diseconomies of customer density, where higher population density slightly increased energy costs.

4.2. Estimation of Water-Energy-Emissions Performance Index (WEEPI)

The main statistics for the estimated WEEPI of both classes of water companies over the study period (2011–2019) are presented in Figure 2. Although both classes displayed high levels of WEEPI, companies in class 1 were on average slightly more efficient than those in class 2. On

[1] WEEPI is a dimensionless index that ranges between 0 and 1.

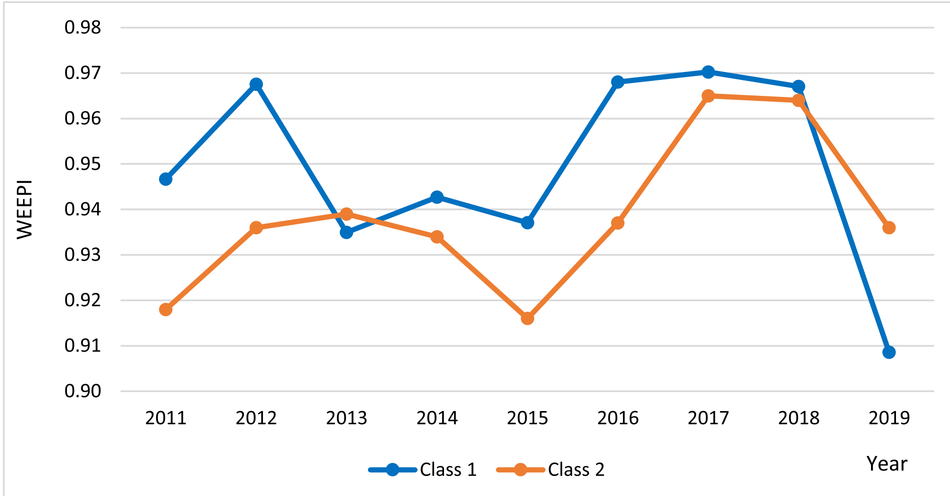

Figure 3. Evolution across years of average Water-Energy-Emissions Performance Index (WEEPI) for water companies embracing class 1 and class 2[2].

average, class 1 companies had a WEEPI of 0.949, indicating that they could improve their efficiency by 5.1%. In contrast, class 2 companies had a slightly lower average WEEPI of 0.938, suggesting a potential efficiency improvement of 6.2%. Despite these relatively high average WEEPI values, no company in either class achieved a WEEPI of 1.0, implying that none of the companies were fully efficient and that there is still room for performance improvements. Among the least efficient firms, the lowest WEEPI in class 1 was 0.729, indicating a potential improvement of 27.1%, whereas the minimum WEEPI in class 2 was 0.897, corresponding to a potential efficiency gain of 10.3%. The differences in WEEPI scores between Class 1 and Class 2 water companies are statistically significant at the 95% confidence level, as indicated by a Mann–Whitney test p-value below 0.05.

Figure 3 illustrates the evolution of the WEEPI for the two classes of water companies between 2011 and 2019. Overall, both classes demonstrated relatively high levels of WEEPI throughout the study period, with Class 1 generally outperforming Class 2. Specifically, Class 1 began at approximately 0.95 in 2011, peaking at nearly 0.97 in 2012 before declining slightly and then rising again to maintain WEEPI values above 0.96 between 2016 and 2018. Class 2 started at a lower level, around 0.92 in 2011, but showed steady improvements, reaching similar levels as Class 1 by 2016 and 2017. Notably, while Class 1 consistently maintained a higher WEEPI than Class 2 for most years, a sharp decline was observed for Class 1 in 2019, dropping to approximately 0.91, whereas Class 2 only experienced a modest decline to around 0.94. These results underscore the overall high performance of both classes but also reveal differences in the stability and evolution of WEEPI between class 1 and class 2 water companies.

The identification of two water companies classes with distinct cost structures and environmental drivers carries important implications for managers. For Class 1 companies, which tend to be larger and more complex, inefficiencies stem mainly from scale diseconomies and operational complexity. For these utilities, management strategies should focus on optimizing existing assets, investing in carbon-efficient technologies, and adopting advanced energy management systems rather than pursuing further expansion. For Class 2 companies, by contrast, results reveal the potential for increasing economies of scale, suggesting that mergers, regional collaboration, or capacity expansion could generate efficiency gains.In terms of regulation, the period 2011–2019 encompasses two price reviews, conducted in 2009 and 2014. The first sub-period, 2011–2014, corresponds to the 2009 price review, during which Ofwat introduced several policies to promote efficiency among water companies. These policies included a rolling incentive mechanism that allowed companies to retain any savings in operating costs, regardless of the year in which these savings occurred (Villegas et al., 2019). Additionally, the regulator strengthened cost reduction targets compared to previous reviews. Figure 3 illustrates that during this sub-period, the WEEPI of class 1 and class 2 water companies displayed distinct patterns. For class 1, WEEPI improved in 2012, reaching a local maximum, but subsequently decreased significantly. In contrast, the increase in WEEPI for class 2 companies in 2012 was more moderate; however, these companies managed to maintain nearly constant efficiency levels until the next price review in 2014.

Several factors may explain the distinct WEEPI patterns observed between class 1 and class 2 water companies during the 2011–2014 period. For class 1 companies, the initial improvements in WEEPI can be attributed to the rapid adoption of new technologies and efficiency practices spurred by the 2009 price review. However, after achieving these early gains, diminishing returns likely set in, making further improvements increasingly difficult and leading to the observed decline in WEEPI. Additionally, the larger operational scale and complexity of class 1 companies may have created challenges in sustaining high efficiency over time, especially as regulatory cost-reduction targets became more stringent. In contrast, class 2 companies, generally smaller in size, may have faced resource limitations that slowed the adoption of new practices but also resulted in steadier, more stable improvements in WEEPI. Their simpler operational structures and more conservative management strategies may have further contributed to their ability to maintain consistent, albeit lower, levels of efficiency throughout the period.

In the second sub-period (2015–2019), corresponding to the 2014 price review, the regulator introduced additional schemes to monitor the economic and environmental performance of water companies. These schemes included financial or reputational rewards and penalties tied to meeting—or failing to meet—targets for various performance indicators, such as water leakage, unplanned interruptions, pollution incidents, and carbon emissions (Ofwat, 2020). The results, depicted in Figure 3, show that water companies in both classes significantly improved their WEEPI through 2018. However, toward the end of the period, performance deteriorated due to rising energy costs and increased GHG emissions. The observed improvements in WEEPI for both classes during the 2015–2019 period can be attributed to the strengthened regulatory framework introduced by Ofwat as part of the 2014 price review. The financial and reputational incentives provided strong motivation for water companies to adopt more energy-efficient

[2] WEEPI is a dimensionless index that ranges between 0 and 1.

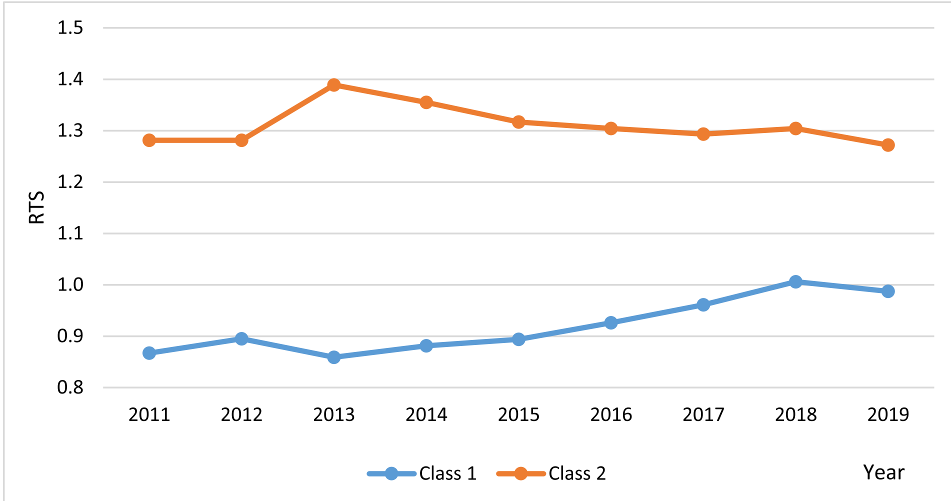

Figure 4. Evolution across years of the average returns to scale (RTS) for water companies embracing class 1 and class 2[3].

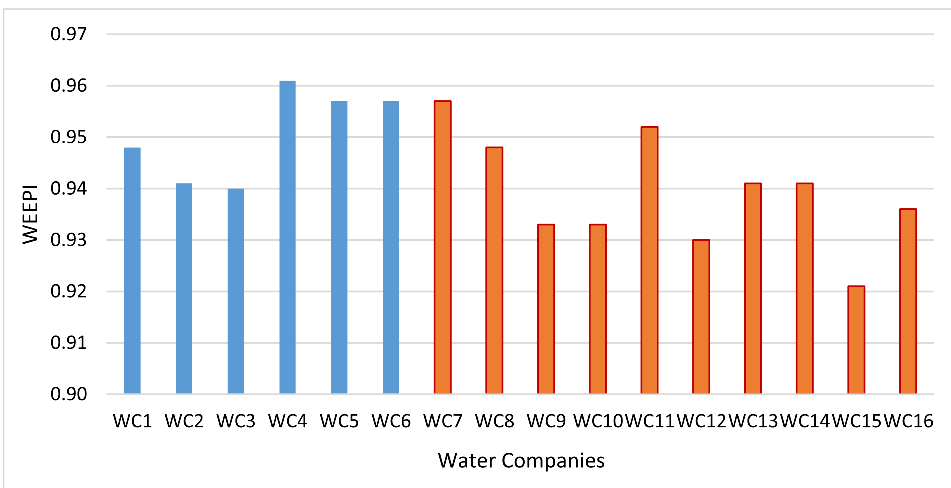

Figure 5. Average Water-Energy-Emissions Performance Index (WEEPI) over the period 2011-2019 for each water company[4].

practices and enhance their environmental performance. Class 1 companies, with larger scale, were likely able to invest more aggressively in technological upgrades and operational improvements, leading to substantial gains in WEEPI. Class 2 firms, although smaller, may have also benefited from these incentives, making steady progress by adopting best practices and improving operational management. However, the decline in WEEPI toward the end of the period suggests that external factors, such as rising energy costs and increasing carbon emissions, began to outweigh these efficiency gains. Additionally, the complexity of sustaining improvements over time, particularly for class 1 companies, may have contributed to the performance decline observed in the final year of the study.

Figure 4 illustrates the evolution of estimated RTS for both classes of water companies over the period 2011–2019, shedding light on the differences in WEEPI performance shown in Figure 3. On average, class 1 companies operated under decreasing economies of scale throughout most of the study period, with RTS values below unity. This indicates that further increases in their operational scale, such as delivering more water to customers, could lead to proportionally higher costs. However, by the end of the period, class 1 firms approached constant returns to scale (RTS $\approx$ 1), suggesting a shift towards their most productive scale. Consequently, business plans for these larger firms should prioritize operational efficiency improvements rather than expansion. In contrast, class 2 companies consistently exhibited increasing economies of scale, with RTS values exceeding 1.2 and peaking at around 1.4 in 2013. This trend suggests that expanding operational scale, for example through mergers or enhanced capacity, could generate substantial cost savings and drive efficiency improvements. The consistent gap in RTS between the two classes highlights structural differences: while class 1 firms face challenges linked to their size and complexity, class 2 firms benefit from opportunities to scale up their operations and leverage economies of scale to improve WEEPI outcomes.

Analysis of the individual water company level also reveals notable findings in WEEPI (Figure 5). Class 1 includes six water companies (WC1–WC6), with WEEPI values ranging from 0.940 to 0.961. Class 2 comprises ten water companies (WC7–WC16), with WEEPI values spanning from 0.924 to 0.957. Despite differences in company size, operational complexity, and external factors, Figure 5 shows that WEEPI values remain relatively close across companies within each class. This consistency suggests that while some water companies demonstrate

[3] WEEPI is dimensionless .

[4] WEEPI is a dimensionless index that ranges between 0 and 1.

slightly higher performance, no company is fully efficient and that there is room for all to improve. Moreover, the relatively narrow range of WEEPI values across firms highlights the sector's overall efforts to achieve and maintain high energy and carbon efficiency, even amid varying environmental and operational conditions.

Several factors could explain the relatively close WEEPI values observed across water companies. Firstly, all water companies in England and Wales operate under a standardized regulatory framework established by Ofwat, which includes uniform incentives and penalties for efficiency, fostering a level playing field. Secondly, the adoption of similar technological and operational practices across the industry, driven by shared standards and widespread availability of best practices, contributes to aligned performance. Additionally, benchmarking and peer-learning within the sector encourage companies to adopt successful efficiency strategies from their peers, reducing performance disparities. The environmental and operational challenges faced by water companies are also largely uniform, creating comparable pressures to enhance energy and GHG emissions performance. National policy initiatives and sector-wide targets for carbon reduction and environmental stewardship further reinforce this alignment, steering all companies toward similar efficiency goals.

Findings from this study underscore the importance of tailoring regulatory frameworks to account for the heterogeneity among water companies. Given that class 1 and class 2 companies exhibit different WEEPI patterns, the water regulator (Ofwat) should consider adopting differentiated regulatory targets and incentives that reflect these structural differences. For example, Outcome Delivery Incentives (ODIs)—which reward or penalize utilities based on environmental and service outcomes—could be recalibrated by class to reflect differing baseline conditions. For class 1 companies, policies should prioritize operational efficiency and carbon reduction through the promotion of advanced technologies and its optimization, recognizing their limited scope for expansion without incurring higher costs. In contrast, class 2 companies may benefit from incentives that encourage operational scaling and strategic mergers, leveraging their observed potential for increasing economies of scale. Additionally, it is highlighted the need for continuous innovation incentives, fostering a culture of ongoing technological improvement to sustain gains in WEEPI across the sector.

Current regulatory frameworks, such as Ofwat's performance commitments and cost assessment models, typically rely on partial performance indicators (e.g., leakage rates, energy use per unit). These approaches may overlook underlying technological heterogeneity and the joint nature of economic and environmental performance. By contrast, the latent-class SFA framework employed in this study estimates a unified input-efficiency index (WEEPI) that integrates labour, energy, and emissions, while accounting for firm-level differences in scale and operational conditions. This provides a more nuanced understanding of performance and supports class-specific policy design. Moreover, by explicitly including GHG emissions as an input to be minimized, WEEPI offers a direct link to carbon pricing and climate policy. Furthermore, Ofwat's Totex framework, which allows cost-sharing of both capital and operating expenditures, could be leveraged to support class-specific decarbonisation pathways. Applying differentiated shadow carbon prices across classes could also help align long-term planning with national net-zero targets, without imposing uniform burdens on structurally different firms. Embedding WEEPI within regulatory reporting could thus align operational performance with the English and Welsh water sector's net-zero 2030 commitment, incentivizing companies to invest in renewables and low-carbon technologies.

Results from this study are also valuable for water companies to enhance their performance. For class 1 companies, with their more extensive service networks and complex operations, improving WEEPI will likely depend on streamlining daily practices, investing in carbon-efficient technologies, and carefully managing network operations to balance water delivery and energy use. Conversely, class 2 companies should explore growth strategies that leverage their potential for economies of scale, such as collaborating with neighboring utilities or expanding their capacity in a sustainable way. Across the sector, companies should continue to prioritize benchmarking and peer learning, adopting best practices that have proven successful in similar operational contexts. Both classes can also benefit from engaging proactively with Ofwat's performance-based incentives and environmental targets, viewing them as opportunities for innovation and long-term sustainability rather than regulatory compliance alone.

A comparison of our results with existing literature reveals both consistencies and distinctions. Sala-Garrido et al. (2023) reported a mean carbon performance score of 0.783 for water utilities in England and Wales under managerial disposability, which is lower than the average WEEPI scores observed in our study (0.949 for Class 1 and 0.938 for Class 2), indicating slightly higher integrated performance in our analysis. Molinos-Senante and Maziotis (2022) found average carbon efficiencies of 0.816 for WaSCs and 0.803 for WoCs, with the latter showing a 2.9% annual improvement in carbon productivity, while WaSCs experienced a 4.2% decline—mirroring the operational challenges we observed among Class 1 companies. Similarly, Maziotis et al. (2023) estimated that carbon inefficiency and energy overuse increased production costs by £0.089/m^3, underscoring the financial implications of inefficiency, which aligns with our findings for Class 1 utilities. Mocholi-Arce et al. (2024) further observed annual dynamic carbon efficiency (DCE) gains of 0.5% for WoCs and 2.4% for WaSCs, comparable to the more stable WEEPI improvements we found among Class 2 companies. Lastly, Molinos-Senante and Maziotis (2023) highlighted the influence of operational and environmental characteristics—such as source water and population density—on carbon performance, which resonates with the class-specific impacts identified in our model. Collectively, these studies reinforce the critical role of operational strategies, targeted regulation, and environmental context in enhancing the sustainability performance of water companies.

5. Conclusions

The transition towards a more sustainable provision of water services requires water companies to be more energy and carbon efficient. This study contributes to the growing body of research at the intersection of energy, carbon, and water by developing and applying a robust latent class stochastic frontier approach to estimate the WEEPI of English and Welsh water companies from 2011 to 2019. Our analysis highlights the significance of accounting for heterogeneity among water companies, an aspect often overlooked in traditional benchmarking exercises. By identifying two distinct classes of companies based on unobserved heterogeneity results reveal that operational complexity and environmental contexts substantially influence performance outcomes.

Results illustrate that, on average, class 1 companies exhibited slightly higher performance than class 2 companies, with average WEEPI scores of 0.949 and 0.938, respectively. Despite these relatively high efficiency levels, there remains scope for improvement. Importantly, the period of the 2014 price review (2015-2019) was associated with improved performance across both classes, suggesting that well-designed financial and reputational incentives can motivate companies to adopt more sustainable practices. However, the decline in WEEPI scores observed toward the end of the period underscores the need for continuous innovation and policy adaptation to ensure that environmental and economic objectives are met in the long term.

Environmental factors such as population density, water treatment complexity, and average pumping head were found to exert varying impacts on the performance of different company classes. For class 1 companies, higher population densities tended to reduce energy costs, suggesting potential economies of density in urban settings. Conversely, class 2 companies appeared more susceptible to inefficiencies stemming from advanced water treatment requirements and environmental challenges related to water abstraction sources. These nuanced relationships underscore the importance of tailoring management strategies and regulatory interventions to the specific environmental contexts of each class.

From a policy perspective, our findings advocate for differentiated regulatory targets and support measures. For class 1 companies, policies should prioritize fostering technological leadership and encouraging investment in carbon-efficient technologies to mitigate the impacts of their operational scale and complexity. In contrast, class 2 companies would benefit from policies that incentivize strategic collaborations and operational scaling to exploit economies of scale and improve energy performance. Across the sector, the findings emphasize the necessity of aligning regulatory incentives with company-specific challenges and opportunities.

Looking ahead, future research should expand the scope of this analysis by incorporating wastewater treatment services, as these activities also represent substantial energy and carbon footprints within the urban water cycle. Moreover, further exploration of additional environmental and operational variables could enhance our understanding of performance drivers and inform more nuanced policy interventions. Nevertheless, the methodology used in this study, i.e., latent class SFA, is fully transferable and can be applied to other utility sectors, countries, or regulatory environments where water-energy-carbon performance must be evaluated under complex and diverse operating conditions.

CRediT authorship contribution statement

Alexandros Maziotis: Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Maria Molinos-Senante:** Writing – review & editing, Visualization, Methodology, Investigation, 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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