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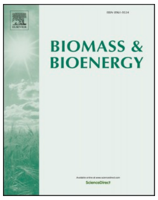

Benchmarking techno-economic efficiency of bioresources management in the water industry: a synthetic index-based approach

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ABSTRACT

The transition towards a circular economy in the water industry has increased the strategic importance of bioresources management, particularly in relation to renewable energy generation and sewage sludge treatment within wastewater services. Despite this relevance, techno-economic performance in bioresources activities has not been systematically assessed. To address this gap, this study introduces the Techno-Economic Bioresource Index (TEBI), a novel benchmarking indicator based on a non-radial Data Envelopment Analysis approach. The framework is applied to a sample of 50 observations operating in England and Wales. The results reveal substantial heterogeneity in performance, with TEBI values ranging from 0.124 to 1.000 and an average score of 0.76, indicating an average improvement potential of approximately 24%. Inefficiencies are found to be variable-specific rather than systemic, with energy utilization, energy export, and untreated sludge emerging as the main sources of inefficiency for several utilities. No relationship is observed between techno-economic efficiency and utility size. A super-efficiency analysis further discriminates among efficient utilities, enabling the identification of robust benchmarks. The findings demonstrate that efficient bioresources management can play a key role in supporting the transition towards a circular water industry, and that TEBI provides a transparent and operational tool to support regulatory benchmarking and evidence-based decision-making.

1. Introduction

The transition from a linear to a circular economy has gained increasing prominence over recent decades due to growing pressure on natural resources [1]. In the European Union (EU), this transition has been further reinforced by the first and second Circular Economy Action Plans adopted in 2015 and 2020, respectively [2]. Within this context, the water sector plays a central role, as recognized by the World Bank's *Water in Circular Economy and Resilience* framework [3]. In particular, wastewater treatment has become particularly relevant to the circular economy transition, as wastewater treatment plants (WWTPs) generate multiple by-products, including treated effluent, biogas, and sewage sludge [4,5]. As a result, WWTPs are increasingly evolving into water resource recovery facilities [6].

In recent years, the circular economy debate in the wastewater sector has been largely dominated by energy recovery through biogas production, particularly in the European context [7–9]. This focus has intensified following disruptions to global energy markets caused by the war between Ukraine and Russia [10]. In response, the European Commission launched the REPowerEU Plan in 2022, aiming to diversify energy supply sources and reduce dependence on external gas suppliers. In parallel, Directive 2024/3019 on urban wastewater treatment introduces, among other requirements, an obligation for treatment facilities to achieve “energy neutrality” at the national sectoral level, thereby increasing reliance on renewable energy generated from internal processes [11].

Beyond renewable energy generation, biogas technologies also play a critical role in sewage sludge management. By converting organic waste into biogas, anaerobic digestion reduces the environmental impacts associated with sludge disposal [12,13]. Global sewage sludge production is projected to reach 127.5 million tonnes by 2030 [14], and such volumes cannot be landfilled without significant environmental consequences [6]. Moreover, the use of sludge as a soil conditioner depends on its content of heavy metals and organic contaminants [15]. In addition, biosolids have emerged as a major anthropogenic pathway for microplastics into terrestrial ecosystems, a phenomenon documented

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across 18 countries and confirmed by field studies conducted over more than two decades [16,17].

Despite the recognized importance of the wastewater sector in the transition to a circular economy, this relevance has not been translated into a universally accepted definition or standardized measurement framework [18,19]. Life cycle assessment (LCA) remains the predominant tool used to evaluate the "circularity" of WWTPs [5,8,20,21], because it captures the full environmental footprint of a wastewater treatment plant across its entire life cycle, while accounting for the environmental impacts of resource recovery strategies central to the circular economy [22]. However, in regulated sectors such as wastewater services, economic considerations are also critical, as service costs are ultimately transferred to consumers through water tariffs [23–25]. To date, only Shrestha et al. [26] has integrated environmental and economic variables to estimate an eco-efficiency index as a circularity metric. In that study, however, the economic variable reflects the cost of achieving carbon neutrality through assigned carbon prices, rather than the actual costs associated with implementing circular economy strategies at WWTP level.

Against this background, four interrelated gaps in the existing literature can be identified, which together motivate the present study. First, despite the growing recognition of the wastewater sector's role in the circular economy, no universally accepted or standardised measurement framework exists for assessing circularity performance in this sector [18,19]. LCA, while valuable for environmental appraisal, does not integrate economic dimensions in a manner relevant for regulated monopolistic utilities, where service costs are ultimately transferred to consumers through water tariffs [23,24]. Second, a substantial body of literature has addressed the overall efficiency of water utilities over the past 25 years [27,28], yet no previous study has evaluated the techno-economic efficiency of water utilities specifically with respect to bioresources activities within a unified analytical framework. This gap is particularly relevant given the strategic importance that regulators such as OFWAT have attributed to bioresources[1] performance [30]. Third, the only study to date that integrates economic and environmental variables to derive a circularity metric for wastewater treatment [26] relies on a proxy cost variable based on assigned carbon prices rather than actual bioresources costs, rendering it unsuitable for peer-based regulatory benchmarking. Fourth, existing performance assessment tools, including ratio-based indicators and radial DEA models, do not allow inefficiencies to be decomposed at the variable level, thereby limiting their capacity to provide regulators and utility managers with actionable, dimension-specific guidance on where improvements are most needed [31,32].

To address these four gaps, this study introduces the Techno-Economic Bioresource Index (TEBI), a novel benchmarking indicator based on a non-radial DEA approach that integrates actual bioresources costs with multiple desirable and undesirable outputs into a single dimensionless score. The TEBI is subsequently decomposed to quantify the variable-specific improvements required for inefficient utilities to reach the efficient frontier. In addition, a super-efficiency analysis is conducted to discriminate among efficient utilities and identify best-performing benchmarks. The index supports performance monitoring by water regulators and facilitates the design of incentives to accelerate the transition towards a circular water industry. Application of TEBI to the English and Welsh water sector demonstrates its potential to support regulatory decision-making, prioritize utility actions, and benchmark circularity within the wastewater sector.

The main contribution of this study is the development and application of the TEBI, a dedicated benchmarking tool designed to assess the techno-economic efficiency of water utilities in bioresources management. The proposed framework integrates renewable energy generation and sewage sludge management within a unified analytical structure. In contrast to existing approaches, which predominantly focus on environmental performance through LCA or rely on proxy economic indicators, TEBI incorporates actual bioresource costs alongside multiple desirable and undesirable outputs within a non-radial DEA model. This approach enables a detailed, variable-specific decomposition of inefficiencies. Furthermore, the study advances conventional efficiency analysis by incorporating a super-efficiency framework, allowing for the discrimination and ranking of efficient utilities, thereby enhancing its applicability for regulatory benchmarking. In addition to the above cited novelties, it is important to distinguish the proposed approach from conventional techno-economic analysis (TEA), which is widely used in the water and energy sectors. Traditional TEA typically focuses on evaluating the economic feasibility of individual technologies or projects through indicators such as net present value, internal rate of return, or cost–benefit ratios. While these approaches provide valuable insights into investment decisions, they do not enable comparative efficiency assessment across multiple water utilities operating under similar regulatory conditions. Moreover, conventional TEA frameworks are generally not designed to simultaneously account for multiple desirable and undesirable outputs, nor do they provide information on best-practice performance or the sources of inefficiency. In contrast, the proposed TEBI adopts a benchmarking perspective based on DEA, allowing for the integration of multiple performance dimensions into a single efficiency score. The non-radial structure of the model further enables the decomposition of inefficiencies at the variable level, thereby providing targeted and operational guidance for performance improvement. This represents a key methodological advancement over conventional TEA in the context of regulating and benchmarking bioresources management in the water industry.

2. Materials and methods

2.1. Methodology

The proposed TEBI is built upon the use of DEA, a well-established methodology for assessing the efficiency of water utilities and particularly suited to their complex, multi-dimensional nature [33–35]. A key advantage of DEA is its non-parametric formulation, which avoids restrictive assumptions regarding the functional form of the production technology or the statistical distribution of inefficiency. Unlike parametric approaches such as Stochastic Frontier Analysis (SFA), which require the priori specification of a production function, DEA constructs an empirical best-practice frontier directly from observed data, providing greater flexibility for benchmarking purposes [36,37]. A further strength of DEA is its ability to simultaneously accommodate multiple inputs and multiple outputs without requiring explicit price or cost information. This characteristic is especially relevant for water utilities, which operate with complex input–output structures that cannot be adequately captured by traditional ratio-based performance indicators [38,39].

DEA models can be classified as radial or non-radial. Radial models assess efficiency by proportionally reducing all inputs (input-oriented) or proportionally expanding all outputs (output-oriented), projecting inefficient decision-making units (DMUs) onto the efficiency frontier. However, this approach neglects potential slacks, defined as residual input excesses or output shortfalls that may remain after proportional adjustment [31,40]. In contrast, non-radial DEA models explicitly account for these slacks, allowing inputs and outputs to adjust by different proportions. As a result, a DMU is deemed efficient only when no further input reductions or output increases are possible without deterioration elsewhere [32,41]. This more granular representation of inefficiency is particularly valuable for regulators and utility managers, as it identifies

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[1] The English and Welsh Water Services Regulation Authority, OFWAT, defines bioresources as outputs from wastewater treatment activities that are separated from core wastewater collection and treatment and which include organic waste (biosolids) with the potential to be repurposed and reused mainly for renewable energy production [29].

specific sources of resource misallocation and supports targeted corrective actions [42,43]. For these reasons, this study adopts a non-radial DEA model to estimate the TEBI.

TEBI framework presents some notable advantages over alternative approaches to assess the performance of water utilities in bioresources activities. Conventional TEA evaluates individual technologies or projects through absolute economic indicators such as net present value or internal rate of return, but does not enable comparative benchmarking across multiple utilities, does not construct a peer-based efficiency frontier, and does not decompose performance gaps at the variable level. Ratio-based KPIs assess performance dimensions in isolation, making it impossible to capture the multidimensional nature of bioresources management in a single internally consistent metric, and are known to produce misleading results when used in standard DEA models for absolute data due to violations of the convexity axiom [44]. Radial DEA models impose proportional adjustments across all inputs or outputs simultaneously and therefore cannot identify dimension-specific inefficiencies or account for residual slacks, limitations that are particularly problematic in the context of bioresources management, where different utilities may be inefficient in entirely different dimensions. Finally, LCA-based approaches capture environmental performance across the full life cycle of a facility but do not integrate actual economic costs, do not construct peer-based efficiency frontiers, and are not designed for comparative regulatory benchmarking across multiple utilities. TEBI addresses all of these limitations simultaneously by combining peer-based frontier estimation, multi-dimensional integration of desirable and undesirable outputs using actual bioresources costs, non-radial slack decomposition enabling variable-specific improvement targets, and super-efficiency discrimination among best-performing utilities.

Consider a set of Decision Making Units (DMUs) denoted as $j = 1, \ldots, n$, each employing m inputs x_{ij} $(i = 1, \ldots, m)$ to generate q_1 desirable products, denoted as $y^g_{r1j}(r_1 = 1, \ldots, q_1)$. As part of the production process, q_2 undesirable products are produced, denoted by $y^b_{r2j}(r_1 = 1, \ldots, q_2)$. Under a traditional additive DEA framework, the following model should be estimated to compute efficiency scores [45]:

$$\max \sum_{i=1}^{m} s^-_{io} + \sum_{r_1=1}^{q_1} s^{+g}_{r_1 o} + \sum_{r_2=1}^{q_2} s^{+b}_{r_2 o} \tag{1}$$

$s.t.$

$$\sum_{j=1}^{n} \lambda_j x_{ij} = x_{io} - s^-_{io} \quad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y^g_{r_1 j} = y^g_{r_1 o} - s^{+g}_{r_1 o} \quad r_1 = 1, \ldots, q_1$$

$$\sum_{j=1}^{n} \lambda_j y^b_{r_2 j} = y^b_{r_2 o} - s^{+b}_{r_2 o} \quad r_2 = 1, \ldots, q_2$$

$$\lambda_j \geq 0, s^-_{io} \geq 0, s^{+g}_{r_1 o} \geq 0, s^{+b}_{r_2 o} \geq 0, j = 1, \ldots., n$$

where s denotes slack variables, representing excess input use, shortfall in desirable outputs, and overproduction of undesirable products. The vector λ contains the intensity variables that are used to construct the efficient frontier as a convex combination of observed water utilities. After solving Model (1), the benchmarking target for a given DMU_o characterized by the observed input-output vector $\left(\overline{x}_{io}, \overline{y}^g_{r_1 o}, \overline{y}^b_{r_2 o}\right)$ is defined as $\left(\overline{x}_{io} - s^{-*}_{io}, \overline{y}^g_{r_1 o} + s^{+g*}_{r_1 o}, \overline{y}^b_{r_2 o} - s^{+b*}_{r_2 o}\right)$, where s^{-*}_{io}, $s^{+g*}_{r_1 o}$ and $s^{+b*}_{r_2 o}$ are the optimal input, desirable output, and undesirable output slacks, respectively.

However, as demonstrated by Aparicio et al. [46], the projection obtained from a standard additive DEA model may not be sufficient to serve as an appropriate benchmark for an inefficient water utilities. In many cases, closer efficient targets exist that provide more meaningful and attainable benchmarks. These targets can be identified by combining the linear convex combinations of extremely efficient water utilities derived from the envelopment model with the input–output weights obtained from the multiplier model [47]. Aparicio et al. [46] and Jahanshahloo et al. [48] further noted that the similarity between the evaluated water utility and its benchmark can be defined using different criteria, such as distance measures or efficiency scores, which leads to alternative model formulations. One such approach consists of identifying the closest projection on the efficient frontier by solving a mathematical programming problem that minimizes the distance between the evaluated DMU and the frontier [45]. In this context, the L_1-distance, defined as:

$$\|x_1\| = |x_1| + \ldots + |x_m| \tag{2}$$

can be used to find the optimal projection and derive efficiency scores [49].

Accordingly, this study adopts a minimum distance–based additive DEA model [46], formulated as a 0–1 mixed-integer linear programming (MILP) problem, to identify the nearest benchmarking targets in the presence of undesirable outputs. The model minimizes the sum of non-radial slacks using the L_1-norm and is defined as follows:

$$\min \sum_{i=1}^{m} s^-_{io} + \sum_{r_1=1}^{q_1} s^{+g}_{r_1 o} + \sum_{r_2=1}^{q_2} s^{+b}_{r_2 o} \tag{3}$$

$s.t.$

$$\sum_{j \in E} \lambda_j x_{ij} = x_{io} - s^-_{io} \quad i = 1, \ldots, m$$

$$\sum_{j \in E}^{n} \lambda_j y^g_{r_1 j} = y^g_{r_1 o} - s^{+g}_{r_1 o} \quad r_1 = 1, \ldots, q_1$$

$$\sum_{j \in E} \lambda_j y^b_{r_2 j} = y^b_{r_2 o} - s^{+b}_{r_2 o} \quad r_2 = 1, \ldots, q_2$$

$$-\sum_{i=1}^{m} v_i x_{ij} + \sum_{r_1=1}^{q_1} u_{r_1} y^g_{r_1 j} + \sum_{r_2=1}^{q_2} z_{r_2} y^g_{r_2 o} + d_j = 0$$

$$v_i \geq 1, u_{r_1} \geq 1, z_{r_2} \geq 1 \quad j \in E$$

$$d_j \leq M b_j$$

$$\lambda_j \leq M(1 - b_j)$$

$$b_j \in \{0, 1\}$$

$$\lambda_j \geq 0, d_j \geq 0, s^-_{io} \geq 0, s^{+g}_{r_1 o} \geq 0, s^{+b}_{r_2 o} \geq 0, j = 1, \ldots., n$$

where E denotes the set of extremely efficient water utilities identified from the optimal solution of Model (1), M is a sufficiently large positive constant, b_j is a binary variable, and $v_i, u_{r_1}, and\, z_{r_2}$ are the multipliers associated with inputs, desirable outputs, and undesirable outputs, respectively.

After solving Model (3), the TEBI for each DMU_o, $TEBI^*_o$ corresponds with the minimum-distance efficiency score computed as follows [45]

$$TEBI^*_o = \frac{1 - \frac{1}{m} \sum_{i=1}^{m} s^{-*}_{io} \Big/ x_{io}}{1 + \frac{1}{q_1 + q_2} \left(\sum_{r_1=1}^{q_1} s^{+g*}_{r_1 o} \Big/ y^g_{r_1 o} + \sum_{r_2=1}^{q_2} s^{+b*}_{r_2 o} \Big/ y^b_{r_2 o} \right)} \tag{4}$$

The $TEBI^*_o$ takes values in the interval (0, 1]. A water utility is considered fully efficient when $TEBI_o^* = 1$, which implies that all input, desirable output, and undesirable output slacks are equal to zero.

In Model (4), each slack is divided by the observed value of the corresponding variable for the DMU under evaluation, so that the TEBI score is expressed as a proportion of current performance and is therefore dimensionless and directly comparable across utilities of different sizes and operational profiles. This normalization is what makes the TEBI a relative rather than absolute measure of efficiency.

As a relative efficiency measure derived from peer comparison, TEBI allows regulators to assess the techno-economic performance of water utilities in bioresources management under monopolistic conditions. Utilities with $TEBI = 1$ define the efficient frontier and represent best-practice benchmarks, while utilities with lower scores are identified as relatively inefficient. The associated slack variables provide quantitative guidance on potential input reductions, desirable output expansions, and undesirable output reductions, enabling regulators to distinguish between performance gaps.

The slack variables represent the magnitude and direction of adjustment required for each input and output variable in order for a given water utility to reach the efficient frontier. In this study, a sign convention is adopted to facilitate interpretation in the results. Specifically, negative slack values indicate the required reduction in inputs or undesirable outputs (e.g., bioresource costs or untreated sludge), whereas positive slack values indicate the required increase in desirable outputs (e.g., energy used, energy exported, or sludge treated). A slack value equal to zero implies that the corresponding variable is already operating efficiently and does not require adjustment. This interpretation allows for a direct identification of variable-specific improvement targets for each water utility.

Because multiple water utilities achieve a TEBI value equal to 1, it is not possible to identify a single best-performing utility using the standard efficiency measure alone. To discriminate among efficient utilities, a super-efficiency analysis is therefore employed. This approach is also based on a DEA framework, but allows efficiency scores, i.e., the TEBI to exceed unity, thereby enabling differentiation among efficient DMUs [50]. In this study, a non-oriented slacks-based measure super-efficiency model is applied [51], which involves solving the following optimization problem:

$$Super-efficiency\ TEBI_0 = \min \frac{1 + \frac{1}{m+q_2}\left(\sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}} + \sum_{r_2=1}^{q_2} \frac{s_{r_2o}^{+b}}{y_{r_2o}^b}\right)}{1 - \left(\frac{1}{q_1}\right)\sum_{r_1=1}^{q_1} \frac{s_{r_1o}^{+g}}{y_{r_1o}^g}} \tag{5}$$

$s.t.$

$$\sum_{j=1, j\neq j_0}^{n} \lambda_j x_{io} - s_{io}^- \leq x_{io}, i = 1, \ldots, m$$

$$\sum_{j=1, j\neq j_0}^{n} \lambda_j y_{r_1o}^g + s_{r_1o}^{+g} \geq y_{r_1o}^g, r_1 = 1, \ldots, q_1$$

$$\sum_{j=1, j\neq j_0}^{n} \lambda_j y_{r_2o}^b - s_{r_2o}^{+b} \leq y_{r_2o}^b, r_2 = 1, \ldots, q_2$$

$$0 \leq s_{r_1o}^{+g} \leq y_{r_1o}^g, s_{io}^- \geq 0, y_{r_2o}^b \geq 0,$$

$$\lambda_j \geq 0, j = 1, \ldots., n, j \neq j_0$$

The TEBI is computed assuming constant returns to scale (CRS) rather than variable returns to scale (VRS) as the intensity variables in models (1, 3 and 5) are constrained only to non-negativity ($\lambda_j \geq 0$). The CRS assumption is adopted on both theoretical and contextual grounds. Theoretically, it allows the efficiency frontier to be constructed without imposing scale restrictions on the reference technology, so that techno-economic efficiency is assessed against a common standard regardless of utility size. Contextually, the regulatory framework applied by OFWAT to bioresources activities benchmarks utilities against sector-wide performance targets rather than size-adjusted ones, making CRS the appropriate specification in this regulatory benchmarking framework. It is acknowledged that a VRS specification would permit the decomposition of overall efficiency into pure technical and scale efficiency components. However, given the regulatory context of this study and the empirical absence of a relationship between TEBI scores and utility size reported in Section 3.1, the CRS assumption is retained as the preferred model specification.

Since TEBI is a newly developed index with no direct precedent in the bioresources benchmarking literature, establishing its validity and accuracy is essential. In the absence of an external gold standard against which TEBI scores could be compared directly, validation is demonstrated through three complementary approaches that collectively provide robust evidence for the credibility of the index. First, theoretical validity is established through the mathematical foundations of the model. The TEBI is derived from the minimum-distance additive DEA framework of Aparicio et al. [46], which satisfies the standard DEA axioms of free disposability, convexity, and minimum extrapolation. The resulting efficiency score is bounded between 0 and 1, is dimensionless, and achieves its maximum value if and only if all input, desirable output, and undesirable output slacks are simultaneously equal to zero. These properties ensure that the TEBI is a mathematically rigorous and economically interpretable measure of relative efficiency.

Second, internal consistency is assessed through the discriminatory power of the index. TEBI scores range from 0.124 to 1.000, with 14 of 50 DMUs (28%) classified as fully efficient. This proportion is consistent with the discriminatory performance typically observed in DEA applications to regulated utilities, and the super-efficiency extension further differentiates among all frontier utilities, confirming that the framework retains discriminatory power across the full score distribution.

Third, convergent validity is established by examining the consistency of TEBI results with patterns reported in the established water utility efficiency literature. The absence of a size-efficiency relationship (correlation = 0.014), the variable-specific rather than systemic nature of inefficiencies, and the identification of a medium-sized utility as the top-performing benchmark are all consistent with findings reported independently in the DEA literature for the water sector [31,32,52,53].

2.2. *Case study and sample description*

The case study covers all water utilities providing wastewater services in England and Wales; therefore, the study area corresponds to England and Wales. This is motivated by the importance that the economic water regulator, OFWAT, has attributed to the regulation of bioresources. In particular, OFWAT considers that the trading of bioresources could represent a significant economic and environmental breakthrough, as market development has the potential to expand low-carbon energy generation while reducing water bills. In line with this objective, and following the 2019 Price Review, OFWAT reformed the regulatory framework for bioresources by introducing a separate binding price control. This reform aimed to promote more commercial arrangements and improve efficiency in the interactions among bioresources activities [30].

Based on data availability, the analysis covers the period 2020–2025 and includes data on bioresources activities submitted by water companies as part of their regulatory reporting requirements. The decision-making units (DMUs) are defined as individual water utilities providing wastewater services in England and Wales. The final sample consists of 10 water utilities observed over the study period, resulting in a panel dataset of 50 DMUs. Data was extracted from OFWAT's regulatory datasets and preprocessed to ensure consistency and comparability across utilities and over time. This process included verification of units of measurement, alignment of variable definitions, and treatment of missing or inconsistent observations. In addition, monetary variables, specifically bioresources costs, were adjusted for inflation using the Consumer Price Index (CPI) to ensure comparability over the study period.

The selection of variables (inputs, desirable outputs, and undesirable outputs) is guided by OFWAT's definition of bioresources, namely outputs from wastewater treatment activities that are separated from core wastewater collection and treatment, and which include organic waste (biosolids) with the potential to be repurposed and reused, primarily for renewable energy production [29]. Accordingly, the TEBI integrates six variables, classified as one input, three desirable outputs, and two undesirable outputs.

The input represents the economic dimension and corresponds to total bioresources costs, encompassing both operational expenditure and capital expenditure as reported to OFWAT. Operational expenditure includes energy costs for operating anaerobic digestion and biogas handling systems, labour, chemicals used in sludge treatment, biosolids disposal and land application costs, and contracted third-party sludge treatment services. Capital expenditure reported on an annualised basis reflecting depreciation and cost of capital, includes investment in anaerobic digestion plants, combined heat and power units, and sludge thickening and dewatering facilities. Thus, this variable captures the full annual economic resources deployed by each utility in carrying out bioresources activities and is expressed in million pounds per year. As reported in Table 1, bioresources costs range from £13.24 million to £177.70 million per year, with a mean of £63.94 million and a standard deviation of £40.40 million, reflecting the substantial heterogeneity in the scale of bioresources operations across the sample.

The three desirable outputs represent variables to be maximised and are defined as follows: (i) energy generated from bioresources and used internally by the utility (mean: 60,625 MWh/year), which reduces reliance on purchased grid electricity; (ii) energy generated from bioresources and exported to the grid or third parties (mean: 71,909 MWh/year), which generates revenue and contributes to low-carbon energy supply; and (iii) sewage sludge treated through anaerobic digestion (mean: 138,060 tonnes/year), which reduces disposal volumes and enables biogas recovery. The two undesirable outputs correspond to variables to be minimised: (i) energy generated from bioresources that remains unused (mean: 60,741 MWh/year), representing irrecoverable value loss; and (ii) untreated sewage sludge (mean: 8250 tonnes/year), representing sludge not processed through anaerobic digestion, with associated environmental and disposal implications. The wide ranges observed across all variables confirm the substantial heterogeneity in the scale and operational profile of bioresources activities across the utilities analyzed, further justifying the use of a peer-based benchmarking approach rather than sector-wide averages.

All data were compiled from the OFWAT website, which provides publicly available regulatory information. A descriptive summary of the variables used in the analysis is presented in Table 1.

3. Results and discussion

3.1. Estimation of the techno-economic bioresource index

Each TEBI score represents the value of equation (4) evaluated at the optimal slacks returned by Model (3), normalised by the observed values of the single input (total bioresources cost, x_{io}) and the five outputs (energy used, energy exported, sludge treated, energy unused, and untreated sludge, y_{ro}^{g} and y_{ro}^{b}) for each DMU. A score of 1.0 indicates that all optimal slacks are simultaneously equal to zero, meaning that no adjustment is required in any variable to reach the efficient frontier. A score below 1.0 indicates that at least one variable has a non-zero optimal slack, with the magnitude of the score reflecting the weighted average of normalised slack values across all six variables.

Fig. 1 presents the estimated TEBI for each of the 50 DMUs analyzed. The results reveal substantial heterogeneity in techno-economic performance across water utilities. TEBI values range from 0.124 to 1.000, indicating a wide dispersion in the efficiency with which bioresources are managed within the English and Welsh water sector. The average TEBI score of 0.76 suggests that, on average, water utilities could improve their techno-economic efficiency in bioresources activities by approximately 24%, assuming that inefficient utilities could converge towards best-practice performance defined by the efficient frontier. This finding highlights a significant, yet unrealised, potential for efficiency gains in the sector, consistent with OFWAT's regulatory focus on improving the commercial and operational performance of bioresources activities (see Fig. 2).

Out of the 50 DMUs analyzed, 14 observations (28%) achieve a TEBI value equal to one, indicating full efficiency under the proposed benchmarking framework. These utilities define the efficient frontier and therefore serve as reference benchmarks for the remaining utilities. The relatively high proportion of efficient DMUs suggests that best practices in bioresources management are already present within the sector, reinforcing the suitability of peer-based benchmarking approaches for regulatory and managerial purposes. The application of a super-efficiency DEA model to discriminate among these efficient water utilities is discussed in Section 3.3.

Despite the observed dispersion in TEBI scores, no relationship is found between techno-economic efficiency in bioresources activities and utility size. The estimated correlation coefficient between TEBI and the number of connected properties is 0.014, indicating the absence of a statistically meaningful association between these variables. This finding is consistent with evidence reported in the broader water utility efficiency literature. For example, Guerrini et al. [52], applying a two-stage DEA to Danish water utilities, found that the efficiency of the water sector was not affected by firm size, and that even in the wastewater sector any size-related effects were context-dependent and not universal. Similarly, studies applied to the English and Welsh water sector have found that scale effects on energy performance are negligible [53], and evidence from Spain indicates that scale properties in wastewater treatment are highly sample- and context-dependent, with several studies reporting constant or near-constant returns to scale [54]. More broadly, Goh and See Ref. [28] confirmed in their bibliometric review that empirical evidence on scale effects in water utility benchmarking is mixed and context-specific, with no consensus that size consistently determines efficiency outcomes. In the specific context of bioresources activities, this result is particularly plausible, as performance in energy recovery and sludge treatment is primarily driven by operational management and technology choices rather than by the overall scale of the utility. This interpretation is reinforced by the super-efficiency analysis

Table 1
Descriptive variables used to compute TEBI.

Type of variable	Variable	Unit	Average	Std. Dev.	Minimum	Maximum
Input	Bioresouce cost	Million £/year	63.94	40.40	13.24	177.70
Desirable outputs	Energy used	Mwh/year	60,625.44	54,700.40	1.00	237,709.00
	Energy exported	Mwh/year	71,909.41	76,803.04	1.00	302,285.07
	Sludge treated	000s ton/year	138.06	92.72	8.59	338.80
Undesirable outputs	Energy unused	Mwh/year	60,741.04	55,683.83	1.00	208,621.00
	Sludge untreated	000s ton/year	8.25	10.28	0.28	34.73

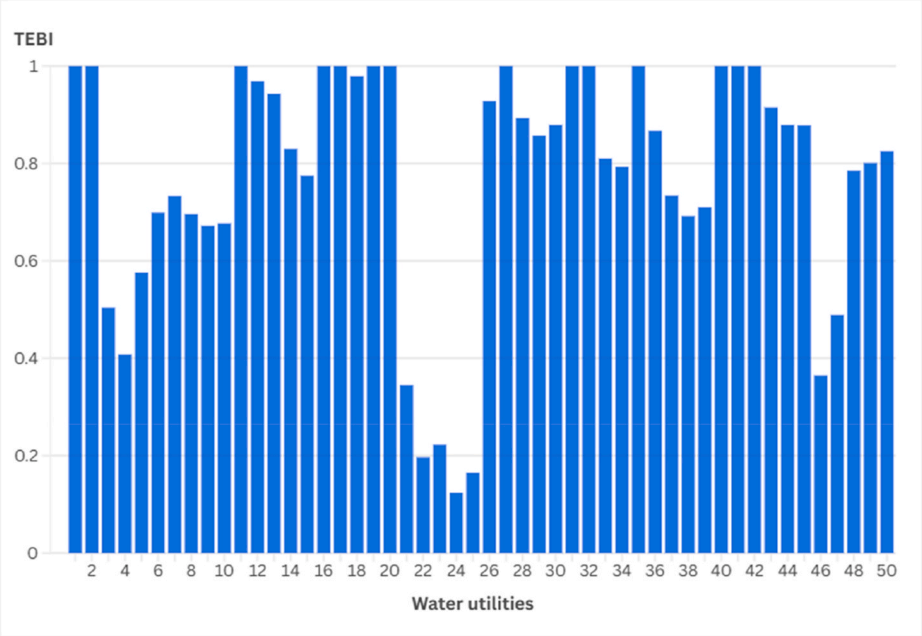

Fig. 1. Techno-economic bioresource index (TEBI) scores for the 50 water utilities analyzed in England and Wales.

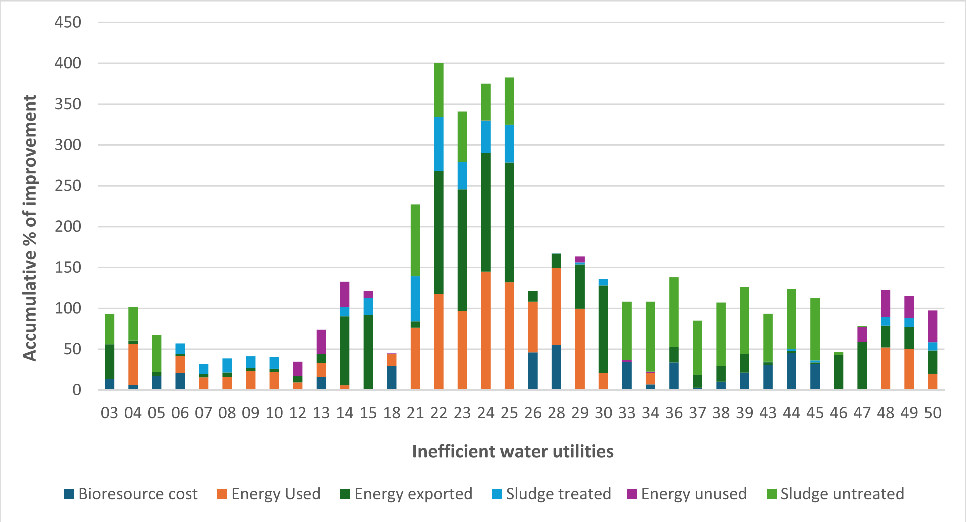

Fig. 2. Accumulative percentage of improvement needed to be techno-economic efficient.

presented in Section 3.3, which identifies a medium-sized utility as the top-performing benchmark.

3.2. Target techno-economic improvement

According to the methodology applied to compute the TEBI, it is possible to estimate, for each inefficient water utility, the slack associated with every variable, which represents the specific improvement required in each dimension to achieve techno-economic efficiency in bioresources activities. Table 2 reports the optimal slack values returned by Model (3) for each inefficient DMU across all six variables. Each column corresponds directly to a specific model component: the Bioresource cost column reports the optimal input slack, where negative values indicate the required reduction in total bioresources cost *to* reach the efficient frontier and zero indicates that cost is already optimal relative to peers. The energy used, energy exported, and sludge treated columns report the optimal desirable output slack where positive values indicate the additional output required to reach the frontier and zero indicates that the output is already at its optimal level. The energy unused and sludge untreated columns report the optimal undesirable output slacks, where negative values indicate the required reduction in undesirable output and zero indicates that the variable is already minimised relative to peers. The percentage values reported in Table 3 correspond directly to the normalised slack terms in Eq. (4).

The results reported in Table 2 reveal a finding of both methodological and regulatory relevance. It is illustrated that none of the water utilities analyzed exhibits inefficiencies across all variables simultaneously. Even among utilities with relatively low TEBI values, at least one input or output dimension operates at an optimal level, as indicated by zero slacks. This finding suggests that inefficiencies in bioresources management are selective and variable-specific, rather than systemic across the entire production process. This result highlights a key advantage of the non-radial DEA framework adopted in this study. Unlike radial models, which impose proportional adjustments across all

Table 2
Optimal slacks for variables embracing the TEBI.

Water utility	TEBI	Bioresource cost (Million £/year)	Energy used (MWh/year)	Energy exported (MWh/year)	Sludge treated (000s ton/year)	Energy unused (MWh/year)	Sludge untreated (000s ton/year)
03	0.504	−13.769	0.000	13931.492	0.000	0.000	−2.489
04	0.408	−6.417	23254.181	1386.381	0.000	0.000	−2.005
05	0.576	−17.356	0.000	1424.107	0.000	0.000	−3.847
06	0.699	−10.940	5217.475	1265.250	8.767	0.000	0.000
07	0.733	0.000	4104.518	1528.924	9.483	0.000	0.000
08	0.696	0.000	4032.819	1790.942	12.418	0.000	0.000
09	0.672	0.000	5159.269	1474.586	10.361	0.000	0.000
10	0.677	0.000	5042.750	1543.620	11.013	0.000	0.000
12	0.969	−0.143	4404.995	1112.765	0.000	−2110.481	0.000
13	0.943	−2.557	8228.982	1391.637	0.020	−3965.773	0.000
14	0.830	0.000	2856.061	9300.733	8.194	−14081.460	0.000
15	0.775	0.000	0.000	11558.699	14.355	−4722.648	0.000
18	0.979	−19.622	8082.934	0.000	0.378	−641.433	0.000
21	0.345	0.000	2111.664	152.591	5.615	0.000	−27.354
22	0.197	0.000	3033.735	1504.483	5.669	0.000	−21.964
23	0.223	0.000	3603.174	1488.248	4.917	0.000	−17.995
24	0.124	0.000	5111.828	1453.815	5.040	−133.359	−12.675
25	0.165	0.000	4600.352	1466.308	5.341	0.000	−20.125
26	0.928	−22.403	25272.115	1474.219	0.000	0.000	0.000
28	0.893	−32.961	32451.011	1492.305	0.157	0.000	0.000
29	0.857	0.000	36960.297	1631.275	2.776	−2350.439	0.000
30	0.879	0.000	10721.963	2202.163	9.246	0.000	0.000
33	0.810	−61.130	0.000	0.000	0.000	−3405.417	−4.058
34	0.793	−7.724	16480.252	0.000	0.000	−2686.787	−9.705
36	0.867	−28.404	0.000	11516.324	0.000	0.000	−12.627
37	0.734	−2.178	0.000	10583.667	0.000	0.000	−8.352
38	0.692	−8.276	0.000	11437.364	0.000	0.000	−16.783
39	0.710	−18.143	0.000	12136.225	0.000	0.000	−19.301
43	0.915	−15.498	0.000	3943.400	0.538	0.000	−6.852
44	0.879	−29.686	0.000	2448.100	1.395	0.000	−13.219
45	0.878	−16.651	0.000	2234.000	1.296	0.000	−15.961
46	0.365	0.000	0.000	2112.343	0.000	0.000	−0.293
47	0.489	0.000	0.000	2072.238	0.000	−26035.722	−0.084
48	0.785	0.000	30528.618	1312.780	14.735	−48458.089	0.000
49	0.801	0.000	30411.972	1273.504	15.400	−34850.061	0.000
50	0.825	0.000	14439.971	1418.034	14.521	−59150.560	0.000

inputs or outputs, the non-radial approach allows for differentiated improvements across variables. As a consequence, utilities are benchmarked only on those dimensions where inefficiencies are observed, while recognizing optimal performance in other dimensions. From a decision-making perspective, this leads to more realistic and actionable efficiency targets, as utilities are not required to modify inputs or outputs that are already operating on the efficient frontier.

At the variable level, the results further indicate that no single variable requires improvement across all utilities. For each of the six variables included in the TEBI there are utilities for which the corresponding slack is equal to zero. This confirms the presence of observable best practices within the sector for each dimension of bioresources management, reinforcing the relevance of peer-based benchmarking approaches.

To further characterize the efficiency gaps identified by the TEBI, the slack values for inefficient utilities are expressed as percentages of current performance levels (Table 2 and Fig. 3). This normalization facilitates a direct comparison across variables and utilities. The results reveal a highly heterogeneous pattern of improvement needs, both across utilities and across variables. For several water utilities, the largest required adjustments are concentrated in a limited number of dimensions, while other variables already operate at optimal or near-optimal levels. This reinforces the earlier finding that inefficiencies in bioresources management are not systemic, but rather dimension-specific.

Across the sample, particularly large improvement requirements are observed for energy-related variables. Several utilities exhibit very high percentages for energy used and energy exported, in some cases exceeding 100% of current values (e.g. DMUs 22–25). This indicates that, relative to best-performing peers, these utilities would need to more than double their effective use or valorization of energy generated from bioresources to reach techno-economic efficiency. Such results point to substantial untapped potential in energy recovery and utilization pathways within the wastewater treatment process. Similarly, sludge management variables show pronounced inefficiencies for a subset of utilities. High required reductions in untreated sludge, often exceeding 70% for several water utilities (e.g. utilities 33–39 and 44–45) suggesting that incomplete treatment of sewage sludge remains a major source of inefficiency. In contrast, other utilities display zero or negligible slacks for this variable, confirming the existence of operational practices within the sector that already achieve efficient sludge treatment outcomes.

The bioresource cost variable also exhibits notable variation. While many utilities show no required cost reductions, others require substantial cost improvements, with values exceeding 40% for some water utilities (e.g. utilities 26 and 28). This dispersion indicates that economic inefficiencies are not uniform across the sector and may reflect differences in contractual arrangements, technology choices, or operational strategies rather than structural constraints.

Fig. 3 illustrates that the cumulative improvement requirements for each inefficient utility arise from different combinations of variables. Importantly, no single variable dominates the inefficiency profile across all utilities. Instead, each utility displays a distinct mix of cost, energy, and sludge-related improvement needs. This visual evidence further supports the appropriateness of the non-radial DEA approach, as it enables the identification of utility-specific improvement pathways rather than imposing uniform proportional adjustments.

Findings from this study demonstrate that performance differences in bioresources activities are driven by utility-specific combinations of operational, technological, and economic factors, rather than by a

Table 3
Reduction percentage for inefficient water utilities.

Water utility	Bioresource cost (%)	Energy used (%)	Energy exported (%)	Sludge treated (%)	Energy unused (%)	Sludge untreated (%)
03	13.30	0.00	42.53	0.00	0.00	37.35
04	6.38	49.82	4.38	0.00	0.00	40.94
05	17.40	0.00	4.49	0.00	0.00	45.34
06	20.93	20.60	2.90	12.61	0.00	0.00
07	0.00	15.51	3.80	12.42	0.00	0.00
08	0.00	16.01	5.50	17.23	0.00	0.00
09	0.00	23.38	3.66	14.19	0.00	0.00
10	0.00	22.16	3.88	14.57	0.00	0.00
12	0.99	8.33	8.23	0.00	17.20	0.00
13	16.19	17.06	10.59	0.03	30.17	0.00
14	0.00	5.78	84.32	11.52	31.11	0.00
15	0.00	0.00	92.11	20.33	8.93	0.00
18	29.64	14.10	0.00	0.14	1.03	0.00
21	0.00	76.40	7.63	55.12	0.00	88.03
22	0.00	117.68	150.45	66.04	0.00	66.00
23	0.00	96.86	148.82	33.71	0.00	61.59
24	0.00	144.93	145.38	38.89	0.70	45.16
25	0.00	131.93	146.63	46.14	0.00	57.95
26	46.05	62.24	13.09	0.00	0.00	0.00
28	54.89	94.39	17.84	0.14	0.00	0.00
29	0.00	99.55	54.14	2.41	7.35	0.00
30	0.00	20.80	107.27	8.15	0.00	0.00
33	34.40	0.00	0.00	0.00	2.14	71.66
34	6.80	13.94	0.00	0.00	1.81	85.63
36	33.73	0.00	19.09	0.00	0.00	85.26
37	2.90	0.00	15.82	0.00	0.00	66.28
38	10.37	0.00	19.20	0.00	0.00	77.46
39	21.34	0.00	22.65	0.00	0.00	81.96
43	30.50	0.00	3.33	0.92	0.00	58.67
44	45.68	0.00	1.83	2.79	0.00	73.25
45	32.05	0.00	1.65	2.54	0.00	76.78
46	0.00	0.00	43.20	0.00	0.00	2.93
47	0.00	0.00	58.81	0.00	18.35	0.84
48	0.00	52.15	26.73	10.27	33.34	0.00
49	0.00	50.20	27.09	11.05	26.58	0.00
50	0.00	20.02	28.32	10.02	38.98	0.00

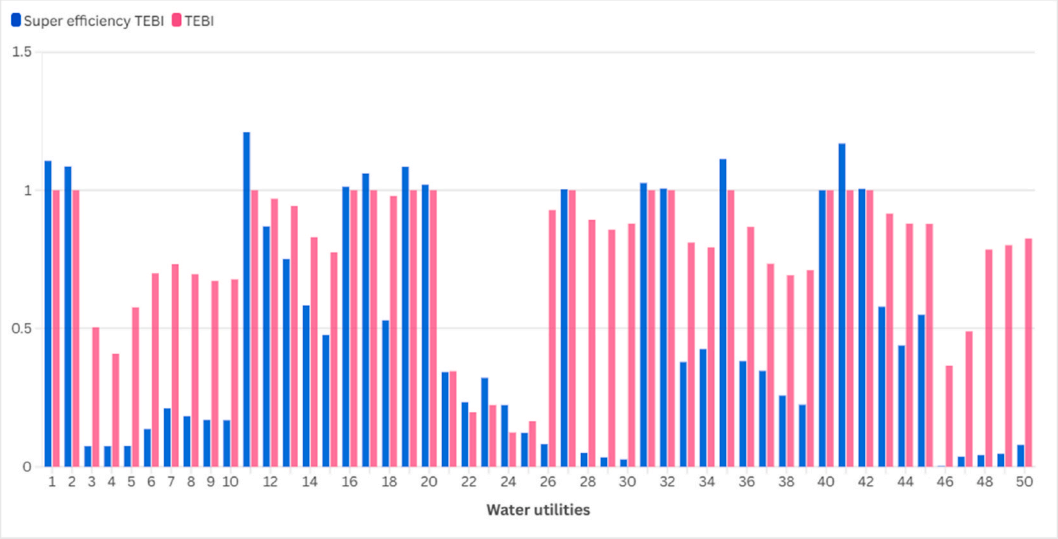

Fig. 3. Super-efficiency techno-economic bioresource index for water utilities.

uniform inefficiency pattern. In this context, TEBI provides a nuanced representation of relative efficiency and supports the identification of targeted improvement pathways. This feature is particularly valuable for regulators, as it enables the design of differentiated incentives and interventions that reflect the specific efficiency gaps of each utility, while avoiding unnecessary or inefficient regulatory pressures on already optimal activities.

3.3. *Discrimination among techno-economic efficient water utilities*

The estimation of the TEBI for the sample of 50 DMUs identifies 14 observations operating on the efficient frontier, all exhibiting a TEBI value equal to 1.0 (Fig. 1). While this result confirms the existence of best-practice performance in bioresources management within the sector, it also implies that standard DEA efficiency scores do not allow discrimination among efficient utilities. Consequently, additional analysis is required to benchmark performance within this group.

To address this limitation, Model (5) is implemented to compute super-efficiency TEBI scores, which are compared with the original TEBI estimates in Fig. 3. The results clearly show that the 14 water utilities initially classified as efficient now exhibit super-efficiency values greater than one, and most importantly, these values differ across utilities. This enables an unambiguous ranking of efficient units, which is not possible under the standard TEBI framework.

Among the efficient utilities, water utility 11 emerges as the best performer, achieving the highest super-efficiency TEBI score of 1.21. This utility can therefore be interpreted as the most robust benchmark in techno-economic bioresources management within the sample. Notably, this utility is of medium size, serving approximately 1.3 million connected properties, indicating that superior bioresources performance is not necessarily associated with scale advantages. A closer examination of its performance profile reveals that its leading position is primarily driven by the minimization of undesirable outputs, as it records the lowest observed levels of both unused energy and untreated sludge. This suggests that its excellent techno-economic performance in bioresources management is strongly linked to effective valorization of energy outputs and comprehensive sludge treatment, rather than to higher input use or scale effects.

More broadly, the dispersion of super-efficiency scores among frontier utilities highlights that not all efficient utilities contribute equally to defining best practice. Utilities with higher super-efficiency values exert a stronger influence on the efficiency frontier, whereas those with values closer to one, although still efficient, represent more marginal benchmarks. From a regulatory and managerial perspective, this distinction is highly relevant, as it supports the identification of priority reference utilities for benchmarking, knowledge transfer, and incentive design.

The combined use of TEBI and super-efficiency analysis enhances the discriminatory power of the benchmarking framework. While TEBI effectively identifies efficiency gaps across the sector, the super-efficiency extension enables a refined assessment of performance among efficient utilities, thereby strengthening the usefulness of the results for regulatory benchmarking and evidence-based decision-making in the transition towards a more circular water industry.

3.4. Policy implications

The results of this study provide several policy-relevant insights for both water regulators and water utilities, particularly in the context of regulating and incentivizing bioresources activities under monopolistic conditions. From a regulatory perspective, the wide dispersion of TEBI scores across the 50 observations indicates substantial heterogeneity in techno-economic performance in bioresources management. This suggests that uniform regulatory requirements or incentives are unlikely to be efficient, as utilities face markedly different performance gaps. Regulators may therefore benefit from adopting differentiated, performance-based regulatory approaches that recognize utility-specific improvement potentials rather than relying on sector-wide averages.

The slack-based analysis shows that inefficiencies are variable-specific rather than systemic. No water utility is inefficient across all dimensions simultaneously, and no single variable requires improvement across all utilities. This finding supports the use of targeted regulatory incentives, focusing on specific dimensions such as energy utilization, energy export, or sludge treatment, instead of imposing proportional efficiency targets across all activities. From a regulatory standpoint, this reduces the risk of imposing unnecessary adjustments on dimensions where utilities already operate efficiently. Moreover, results reveal that energy-related variables (energy used and energy exported) often require the largest adjustments, indicating that, relative to best practice, several utilities exhibit significant untapped potential in bioenergy valorization. Regulators may therefore consider prioritizing incentives or monitoring mechanisms that specifically address the effective use and commercialization of energy generated from bioresources, consistent with the objectives of bioresources market development. Finally, the absence of a statistically meaningful correlation between TEBI and utility size implies that scale is not a determinant of techno-economic efficiency in bioresources management. This finding is particularly relevant for regulatory design, as it suggests that efficiency improvements can be achieved across utilities of different sizes without relying on consolidation or scale expansion. Regulatory benchmarking can therefore remain focused on operational and technological performance, rather than size-adjusted metrics.

For water utilities, the results highlight that efficiency improvements are achievable through selective interventions, rather than comprehensive restructuring of bioresources activities. The presence of zero slacks in several variables for most utilities indicates that many already possess partial best practices that can be built upon. The percentage-based slack analysis provides utilities with clear, quantitative guidance on where improvements are most needed. For some utilities, priorities lie in increasing internal energy use or energy exports, while for others the main inefficiencies are associated with untreated sludge or excessive bioresources costs. The identification of a best-performing utility through super-efficiency analysis reveals that the leading performer is not the largest utility. Thus, high performance is attainable without scale advantages, reinforcing the role of operational management and technology choices. Utilities can therefore use peer benchmarks to guide incremental improvements based on proven practices rather than aspirational or theoretical standards.

The results obtained from the TEBI framework enable the identification of concrete, variable-specific interventions to improve techno-economic performance in bioresources management. For instance, utilities exhibiting high levels of unused energy may prioritize investments in energy storage systems, enhance process integration to increase internal energy utilization, or expand infrastructure for exporting surplus energy to the grid. In cases where low levels of energy use or export are observed, improvements may involve optimizing anaerobic digestion performance, upgrading biogas recovery technologies, or enhancing operational control of energy conversion processes. Similarly, elevated levels of untreated sludge indicate the need for capacity expansion in sludge treatment facilities, adoption of more efficient treatment technologies, or improvements in sludge handling and logistics. From an economic perspective, utilities with significant inefficiencies in bioresource costs may implement cost-optimization strategies, including process optimization, renegotiation of service contracts, or the adoption of more cost-efficient technologies. Collectively, these examples illustrate how TEBI results can be operationalized into targeted technological, operational, and managerial actions aimed at enhancing overall techno-economic efficiency.

4. Conclusions

This study presents the first comprehensive assessment of the techno-economic efficiency of bioresources activities in the water industry, addressing a critical gap in the literature at the intersection of circular economy, wastewater treatment, and economic regulation. While previous research has predominantly focused on environmental performance or overall utility efficiency, this work specifically examines how water utilities manage bioresources within a unified techno-economic framework. To this end, the study introduces the TEBI, a novel benchmarking indicator based on a non-radial DEA approach. TEBI integrates actual bioresources costs with multiple desirable and undesirable outputs, capturing the multidimensional nature of bioresources management in wastewater treatment processes. By explicitly accounting for slacks, the proposed framework allows inefficiencies to be decomposed at the variable level, thereby providing actionable insights beyond aggregate efficiency scores.

Application of TEBI to a sample of 50 DMUs operating in England and Wales reveals substantial heterogeneity in techno-economic performance. TEBI values range from 0.124 to 1.000, with an average score of 0.76. While 14 utilities achieve a TEBI value of 1.0, super-efficiency scores reveal meaningful differences among them, enabling an unambiguous ranking of best performers. A key finding is that inefficiencies in bioresources management are variable-specific rather than systemic. None of the utilities analyzed is inefficient across all dimensions simultaneously, and no single variable requires improvement across all utilities.

The analysis of slack values further clarifies the nature of these efficiency gaps. Energy-related variables, particularly energy used internally and energy exported, often require the largest adjustments. This indicates substantial untapped potential in the valorization of bioenergy generated from wastewater treatment processes. Similarly, untreated sludge remains a major source of inefficiency for a subset of utilities, whereas other utilities demonstrate that efficient sludge management outcomes are already achievable within the sector. In contrast, bioresources costs exhibit wide variation, suggesting that economic inefficiencies are driven by utility-specific operational and strategic factors rather than structural constraints.

From a policy perspective, this study demonstrates that efficient bioresources management can play a crucial role in supporting the transition towards a circular water industry. By providing the first dedicated techno-economic benchmarking framework for bioresources activities, TEBI offers a transparent and operational tool to support evidence-based decision-making by both regulators and water utilities.

A limitation of this study relates to the nature of the data available for analysis. The TEBI was estimated using publicly available regulatory data published by OFWAT, which provides financial and quantitative performance indicators for bioresources activities but does not include process-level or technology-specific information at the utility level. Consequently, it was not possible to investigate the operational or technological factors, such as digestion technology type, feedstock composition, biosolids classification, or waste stream characteristics, that may distinguish efficient frontier utilities from their less efficient peers. Future research should therefore seek to integrate process-level and technology-specific data within the TEBI framework, in order to identify the operational and technological drivers of techno-economic efficiency in bioresources management and to provide utilities and regulators with more targeted guidance on best-practice implementation.

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CRediT authorship contribution statement

María Molinos-Senante: Conceptualization, Formal analysis, Funding acquisition, Methodology, Writing – original draft. **Alexandros Maziotis:** Conceptualization, Methodology, Writing – review & editing.

Data availability

Data will be made available on request.

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