DOCTOR OF PHILOSOPHY

Analysing the water-energy nexus: Benchmarking efficiency in water services

Walker, Nathan

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A thesis submitted to Bangor University by
Nathan Luke Walker

In candidature for the degree of
Doctor of Philosophy

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Abstract

The water and sewage industry has fundamental links to all aspects of sustainability, being responsible for delivering potable water and treating wastewater, a social necessity, which requires significant amounts of energy, physical infrastructure, and financial investment. By utilising benchmarking and performance analysis, companies can identify and prioritise areas for improvement and learn from best practices.

This research embraces and expands on these themes over four main results chapters. Chapter 3 evaluates the economic and emission performance of UK and Irish water companies and identifies the key factors that affect their performance using a double-bootstrapped data envelopment analysis approach. That chapter found the companies could reduce economic and environmental inputs by 19.4% and 15.8% and provides an elementary framework to assess the influence of rurality on operational efficiency, applying it across a set of English and Welsh water companies. Chapter 4 again uses double-bootstrapped data envelopment analysis but evaluates the energy and economic efficiency of water (only), and water and sewerage, utilities in England and Wales, along with appraising the role of some rarely assessed explanatory factors. For example, results suggested that the proportion of water passing through the largest 50% of treatment works exhibited a significant negative effect on economic efficiency and average pumping head height had a significant negative effect for energy efficiency. Moreover, Chapter 4 determines the extent to which proxies may influence efficiency rankings and their determinant variables. Chapter 5 uses several sets of variables within the scope of the Hick-Moorsteen Productivity Index to examine the best approach for a comprehensive sustainability evaluation. Additionally, it investigates productivity change on a sample of UK water companies and disaggregates results for individual companies allowing an investigation of areas for improvement, indicating that the sample improved by 1.8% between 2014-18. Chapter 6 uses 350 companies from 42 countries to explore the energy intensity and reasons for varying performance of wastewater treatment on an international scale, using the most up-to-date data available and an effluent quality control to align performance. The global average electricity consumption for wastewater treatment was 0.89 kWh/m^3 however, EU companies had the highest average energy intensity at 1.18 kWh/m^3. Furthermore, Chapter 6 assesses the carbon impacts of energy intensities across regions and evaluates areas for improvement in international benchmarking practices.

Collectively, the research presented in this thesis can be of use to water industry operators, regulators, benchmarking organisations, and academics by providing new insight into water-energy efficiency within the water sector, and by developing improved methodologies for efficiency benchmarking.

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Abbreviations

AWWA	American Water Works Association
ADERASA	Regulación de Agua y Saneamiento en las Américas
BOD	Biological Oxygen Demand
COD	Chemical Oxygen Demand
CO_2	Carbon Dioxide
CAPEX	Capital Expenditure
CRS	Constant Returns to Scale
DANVA	Danish Water and Wastewater Association
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DWTP	Drinking Water Treatment Plant
EBC	European Benchmarking Co-operation
EPA	Environment Protection Agency
ERSAR	Entidade Reguladora dos Serviços de Águas e Resíduos
EU	European Union
GHG	Greenhouse Gas
GWh	Gigawatt hours
GWP	Global Warming Potential
HMPI	Hick-Moorsteen Productivity Index
IBNET	International Benchmarking Network
IDB	Inter-American Development Bank
IME	Input-oriented Mix Efficiency
ISE	Input-oriented Scale Efficiency
ITE	Input-oriented Technical Efficiency
IWA	International Water Association
KPI	Key Performance Indicator
LPI	Luenberger Productivity Index
Ml	Megalitre
MLSOA	Middle Layer Super Output Area
MPI	Malmquist Productivity Index
OFWAT	Office of Water Services

OPEX	Operational Expenditure
PWWA	Pacific water and wastes association
RISE	Residual Input-oriented Scale Efficiency
RME	Residual Mix Efficiency
RUC	Rural-Urban Classification
SD	Standard Deviation
SDG	Sustainable Development Goal
SEAWUN	South East Asia Water Utility Network
SFA	Stochastic Frontier Analysis
SIM	Service Incentive Mechanism
TECH	Technical Change
TFP	Total Factor Productivity
TFPE	Total Factor Productivity Efficiency Change
TOTEX	Total Expenditure
UK	United Kingdom
UN	United Nations
US	United States (of America)
UWWTD	Urban Waste Water Treatment Directive
VRS	Variable Returns to Scale
WaSC	Water and Sewage Company
WUP	Water Utility Partnership for Capacity Building in Africa

1. Introduction

1.1. Study context and justification

The concept of the water-energy nexus is integral to move towards global environmental sustainability. It encompasses and highlights the intrinsic relationship that water and energy have, that being water is needed for each stage of energy production and energy is fundamental in the provision and treatment of water (IEA, 2016). Until just a decade or two ago, the water-energy nexus was discussed predominantly in relation to hydroelectricity generation; however, in recent years, there has been focus on water in the context of energy-consumption, rather than just production (Cabrera *et al*., 2010). Having this definition and approach towards achieving sustainability means that both water and energy will both be considered more holistically together. It will also allow innovative solutions to be sought that span various dimensions of sustainability, a logical step for this inherently interdimensional concept.

The more exhaustive view of the water-energy nexus (Figure 1.1) has highlighted the importance of the significant amounts of energy that are used to extract, pump and treat supply water and wastewater. In the UK for example, the water industry produced 2.9 Megatonnes of CO_2 in 2020 due to energy usage (DiscoverWater, 2021; Northern Ireland Water, 2021; Scottish Water, 2021), which is approximately 0.83% of national emissions (calculated with data from the Department for Business, Energy, and Industrial Strategy, 2020). The US Environment Protection Agency (EPA, 2018) estimated that 2% of total energy use within the US is a result of drinking water treatment plants (DWTPs) and wastewater treatment plants (WWTPs), whilst within individual municipalities they are some of the largest energy consumers, typically accounting for 30–40% of municipality energy consumption. The global perspective is even more striking, with the United Nations stating that approximately, 8% of global primary energy supply is used to deliver and treat water (UN Water, 2014; UNESCO, 2014). In addition to the energetic costs, there are significant economic and social effects associated with water supply and treatment. Hundreds of billions of dollars are spent each year globally, with more expected in the near future to raise the reliability of supply and sanitation standards (Sedlak, 2014; Cazcarro, 2016).

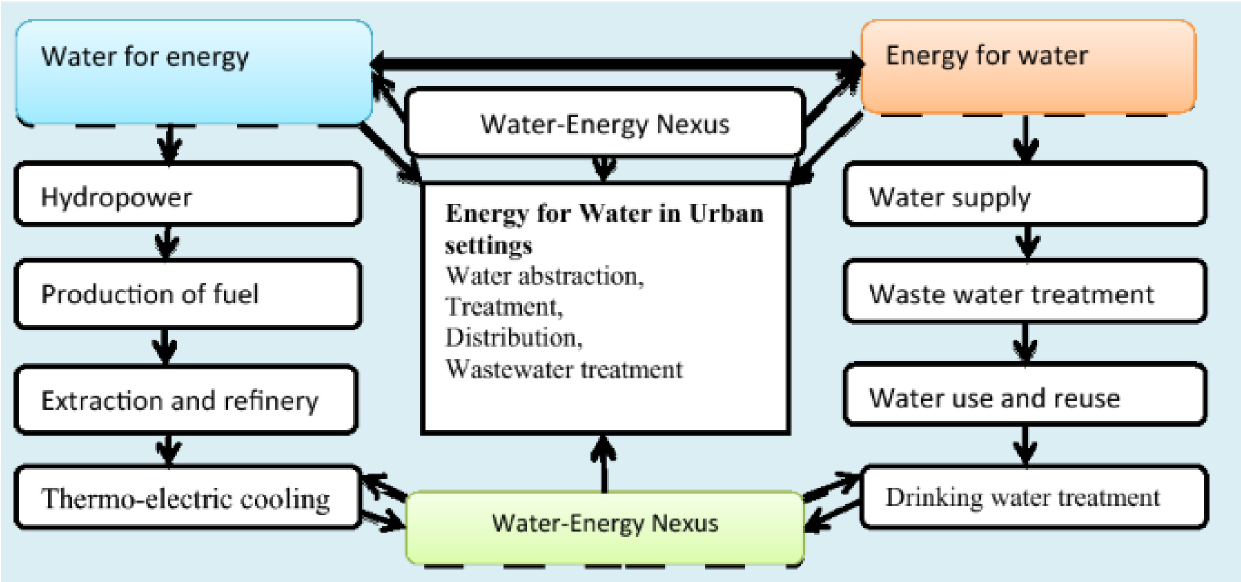

Figure 1.1. *A summary schematic of the water-energy nexus from Fayiah et al. (2020).*

The importance of the water sector is further highlighted with the role it has in the United Nations (2021) 17 Sustainable Development Goals (SDGs), where it thematically touches on several separate goals. The responsibilities and effects of water companies relative to the research presented in this thesis are mostly embedded within SDG 6 (clean water and sanitation for all), which comments on improving water affordability, equity, quality, pollution, and co-operation. In addition to SDG 6, SDGs 7 (access to affordable, reliable, sustainable, and modern energy for all), 11 (make cities inclusive, safe, resilient, and sustainable), and 13 (take urgent action to combat climate change and its impacts), are all impacted by the water sector. These overarching SDGs have manifested in many countries having explicit targets for example, the UK has a legally binding 2050 target of net zero operational emissions, and the UK water sector has committed to achieving this by 2030, which is expected to reduce greenhouse gas (GHG) emissions by 10 million tonnes (Water UK, 2021). Furthermore, the UK water industry has a focus on investing in capital projects in the upcoming years to drive future growth due to the need to increase the infrastructural resilience and increase intergenerational fairness (Wallace, 2021).

For the water sector to improve economically, socially, and environmentally, whilst working towards the UN, national, and regulatory targets, improving efficiency is integral. The England and Wales water regulator, Office of Water Services (OFWAT), has been pushing for this for decades and it is still at the forefront of their objectives, albeit largely based around economic efficiency and productivity (OFWAT, 2020a). To achieve sustainability and the various targets laid out, an understanding of performance is required. Water companies though, whether they are only supplying water or also treating wastewater, are highly complex systems with many inputs and outputs, which are made more difficult to analyse under the scope of their many deliverables to stakeholders (Figure 1.2) including, shareholders, regulators, and the public they serve. This is particularly problematic with the conflicting interests of various stakeholders, e.g., that of the investors, wanting maximum yield returns on investment, environmental groups who want more investment in infrastructure to increase resilience and protect the natural environmental, and customers who want the best service for the lowest cost. To fully understand the operation of these systems, benchmarking leading to holistic efficiency assessment can be valuable tools; different methods to conduct this have been developed and tested to varying degrees of success, which are further discussed in the literature review. This thesis offers varying paths to analysing performance through a variety of methods, groups of indicators, and samples.

Figure 1.2. *A summary of the water industry stakeholders (United Utilities, 2021).*

1.2. Research aims and objectives

The overarching aim of this thesis is to holistically analyse the efficiency of water companies to recommend routes to improvement and ultimately, reduce resource use. To achieve this, the thesis will address the following research objectives:

i. To evaluate the most appropriate methods to conduct multiple input and output analyses of water companies;
ii. To analyse the environmental, social, and economic efficiency of UK water companies;
iii. To assess the role of explanatory factors on water company economic and environmental efficiency;
iv. To review the most appropriate indicators to be used in performance assessment;
v. To conduct an international wastewater energy benchmarking exercise.

1.3. Thesis structure

This thesis consists of eight chapters. The first (current) chapter provides context and justification to the research, gives a brief introduction of the effects and responsibilities of the water sector, and outlines the overarching aim and objectives. Chapter 2 provides a literature review of the themes appropriate to this thesis, covering a summary of performance analysis and benchmarking, relevant methods, and background to the UK water sector. More specific literature reviews and methodologies are present within each results chapter (3, 4, 5, 6). Chapter 3 explores the economic and environmental (carbon in this instance) efficiency of UK and Ireland water companies with a one-year snapshot. Furthermore, it analyses the influence of several explanatory factors, with a particular focus on rurality. Chapter 4 investigates economic and energy efficiency of water only companies (WoCs) and water and sewage companies (WaSCs). Additionally, this chapter assesses explanatory factors, some of which are unique, along with common proxy indicators to test their accuracy. Chapters 3 and 4 utilise a variation of a methodology (date envelopment analysis) that has been rarely applied to water companies and builds upon previous work. Chapter 5 uses an alternative method to analyse efficiency over a 6-year period with eight separate sets of indicators and appraises the best set for a sustainability assessment. Chapter 6 conducts international energy efficiency benchmarking on wastewater treatment and investigates the effect of company size and the level of treatment. Chapter 7 provides an overall discussion of the findings from the results chapters and examines them within the context of the existing literature. It also discusses the outputs of the research and how they can assist the water sector, regulators and analysts. Finally, Chapter 8 addresses how the aims outlined in Chapter 1 have been met and recommends concepts and improvements for future research. This is rounded off with an overall conclusion, featuring the novel study elements and implications of the research.

2. Literature Review

2.1. Benchmarking background

Benchmarking is the process of measuring performance against a standard, which can be either absolute or relative to other similar companies and systems (Wiedmann *et al.,* 2009). These comparisons can be internal within the same organisation or external for an industry-wide assessment. It should be emphasised that benchmarking is a continuous exercise of data collection and analysis, which can establish the difference between potential and current performance level. Used in this manner, benchmarking can be a key efficiency tool (Zhu, 2014). It offers many positives such as assessing performance objectively, exposing areas where improvement is needed, and identifying other companies who are performing better and therefore demonstrating potential adoption strategies (Ecorys, 2012). Additionally, benchmarking, by extension, is about sharing information and building stronger links with the different stakeholders of an industry (or beyond). By following this, the fundamental positives of searching for the best practices in a defined industry can be achieved, and everyone can benefit from it. The Global Benchmarking Network (2021) summarise the direct and indirect benefits of benchmarking. Direct benefits include the company is analysed, comparisons are made, best practices and performance deficits are identified, and alternative solutions are evaluated. Whereas the indirect benefits are promoting an understanding of company processes, questioning objectives of the company, verifying strategy, strengthening competitive position, and initiating the process of continuous improvement.

There are two overarching types of benchmarking that are used: metric and process. Metric benchmarking is the quantitative measurement of performance over time against other similar systems or companies. This method enables information on performance gaps to be gathered and goals to be defined (Hervani *et al.,* 2005). Metric benchmarking does not usually supply a detailed understanding of the variables that may explain differences in the benchmarking results such as physical characteristics, geography, weather, and number of customers, which are known to influence water companies (Berg, 2013). This is why some academics like Kingdom (1998) emphasise the need to use metric benchmarking sparingly especially when assessing water networks as the operating environment significantly influences the performance of indicators. Comparatively, process benchmarking essentially uses data from the metric benchmarking showing where the performance gaps are and identifies specific processes that are to be improved via a detailed step-by-step analysis of sub-processes (Lambert, 2008). This targeted assessment of sub-process performance as well as a review of best practice in external examples identifies at what level or efficiency the process should be operating. Lastly, an implementation plan is undertaken and executed to adapt the processes to a standard revealed by the 'best practise' external company, which is often in direct and open relationships with other companies (Berg, 2013). Parena *et al*. (2002) clearly summarise the differences between the two types of benchmarking by explaining that metric benchmarking identifies the areas of under-performance and where changes need to occur within the whole company or system, whereas process benchmarking is used as the medium to drive this change. Despite metric and process benchmarking being accepted as valid concepts by many of those who carry out benchmarking, the International Water Association (IWA) Specialist Group on Benchmarking actually recommends abandoning the use of these terms (Cabrera Jr *et al.,* 2011). They suggest that 'performance assessment' and 'performance improvement' should be seen as the major components of benchmarking instead, which would ensure a focus on a holistic approach where systems are fully understood and enhanced.

The benefits are so widely understood that benchmarking is common practice in many industries and sectors now as a tool to optimise their resources and achieve ambitious goals (Castro and Frazzon, 2017). The availability and analysis of "Big data", referring to data sets with more varied and complex structures, which are used to reveal hidden patterns and secret correlations (Sagiroglu and Sinanc, 2013), is part of this benchmarking uptake, since the ability to capture and process information has increased, whilst the cost of doing so has reduced, meaning technologies that make benchmarking more precise, detailed and affective are now more widely available (Taylor and Schroeder, 2015). Berg (2013) emphasises the importance of data within the water industry, commenting that if managers do not have enough data for benchmarking and comparison against other companies, one must question what they are actually managing. He further states that if regulators cannot determine historical trends, the current baseline, and relative performance among companies, it is, as an Indian regulator said, like writing "orders that are just pretty poetry".

There are many water utility benchmarking organisations currently in operation that attempt to collect more data and improve performance comparisons both within and between countries. A few notable national level benchmarking examples are within England and Wales via Office of Water Services (OFWAT), Portugal by Entidade Reguladora dos Serviços de Águas e Resíduos (ERSAR), Denmark by Danish Water and Wastewater Association (DANVA), the US through American Water Works Association (AWWA), and New Zealand by Water New Zealand. In addition, there are many cross-boundary benchmarking institutions too such as the EU Benchmarking Co-operation, South East Asia Water Utility Network (SEAWUN), Regulación de Agua y Saneamiento en las Américas (ADERASA), Pacific water and wastes association (PWWA), International Benchmarking Network (IBNET), and AquaRating by the IWA and Inter-American Development Bank (IDB). To affectively compare and find best practices within the water industry, it is important to have a framework that ensures comparison of “apples with apples”. This is a big challenge when benchmarking is already practiced by different organisations and there is a desire to compare them which is why initiatives that aim to set worldwide standards are valuable (Danilenko *et al*., 2014). The various institutions mentioned above conduct important data collection and dissemination in their respective regions however, many only essentially represent a preliminary performance assessment. They enable metric benchmarking, which gives a good overview, but there is a lack of detailed accounting for explanatory factors and paths to better performance, which would be unveiled by process benchmarking and more detailed analytical techniques.

To collect the correct data to conduct sophisticated efficiency performance analysis techniques, key performance indicators (KPIs) are used. There are many definitions for KPIs but generally, they are defined as a quantifiable measure used to evaluate the performance of a certain aspect of a system or organisation (Gunasekaran and Kobu, 2007). To analyse a system holistically, a good set of these indicators needs to be used that not only measure the integral elements, but also do it in such a way that properly represents performance in relation to the rest of the system (Franceschini *et al*., 2007). There are many in current use today to measure water utilities that cover financial, environmental and social aspects of companies (Alegre *et al*., 2017). For example, in 2017, the KPI institute published a report on international water utility benchmarking, which included 178 KPIs within five clusters based on: customers, operations, environment, human capital, and corporate governance. A key global body who specialises on performance assessment and benchmarking indicators is the IWA, have also documented a KPI list of over 170 (Alegre *et al*., 2017). They also have many publications on assessing water utilities such as ‘Water Utility Benchmarking’ (Berg, 2013), ‘Process Benchmarking in the Water’ (Parena *et al*., 2002), and ‘AquaRating: An International Standard for Assessing Water and Wastewater services’ (Krause *et al*., 2015), to name just a few. Having sufficient indicators to cover enough important data in a suitable methodological framework, whilst being refined enough to not dilute the quality of outcomes, is integral for future benchmarking and affective results. This is where academia has attempted to contribute to benchmarking and performance analysis through varied and extensive research.

2.2. Water benchmarking in academia

Several scholars have produced extensive literature reviews on performance analysis of the water and sewage sector (Abbott and Cohen, 2009; Walter *et al*., 2009; Berg and Marques, 2011; Carvalho *et al*., 2012; Worthington, 2014; Cetrulo *et al*., 2019), with Goh and See (2021) being the latest. They reviewed 142 scientific articles and highlighted the research hotspots (Figure 2.1), and one of the most frequently featured concepts is Data Envelopment Analysis (DEA). DEA is a non-parametric programming method used to evaluate the efficiency of homogenous decision-making units (DMUs) (Charnes *et al*., 1978), which within the subject matter, are water utilities. Examples of the use of DEA include Berg and Lin (2011), and Lannier and Porcher (2013), who use DEA and stochastic frontier analysis (SFA) to analyse performance across Peruvian and French water utilities, respectively. The mathematical framework and methodology of DEA has been advanced in recent years. For example, Pointon and Matthews (2016) ascertained optimum resource allocation by introducing intertemporal effects of capital into a dynamic DEA model. Likewise, Deng *et al*. (2016) and Kamarudin *et al*. (2015) used the DEA-directional distance function and slack-based measure, respectively, to analyse undesirable and unexpected outputs. Moreover, Gidion *et al*. (2019) used a network DEA model, a first with water companies as the subject matter.

Figure 2.1. *A summary of water utility benchmarking within academic literature between 2000-2019 from Goh and See (2021).*

The advantages and disadvantages of DEA are discussed more thoroughly within Chapters 3 and 4, so are not investigated extensively here to avoid repetition. Generally though, DEA is favoured within the water benchmarking literature for two reasons. Foremost, the method allows the integration of multiple input and output combinations to the scalar measure of relative efficiency in the production frontier. Additionally, DEA does not require *a priori* assumptions about the functional form of their production or cost, whereas SFA, another popular choice, does (Cooper *et al*., 2011). The main limitation is that it is sensitive to outliers because of the lack of statistical inferences, which can lead to biased estimations (Yang *et al*., 2014). To overcome this drawback, non-parametric partial frontier methods can be used, which are derived from the concept of defining the production process by a probabilistic formulation, initially proposed by Cazals *et al*. (2002). These methodologies are part of the order-α and order-m methods, and do not envelop all the sample data to estimate the production frontier, thus becoming less sensitive to extreme data. Carvalho and Marques (2014) used this partial frontier approach to analyse scope and scale economies in the

Portuguese water sector. Another approach to overcome the biases that can arise using DEA are bootstrap algorithms (Simar and Wilson, 2007). They have been sparsely applied to the water sector (See, 2015; Molinos-Senante *et al*., 2018a; Villegas *et al*., 2019), which is one of the ways Chapters 3 and 4 add value to the literature. More details on the specifics of the methodology can be found in those chapters.

The condition of research on water utility performance has clearly developed over the past few decades. However, Goh and See (2021) found that almost all the studies they reviewed had benchmarked the performance of water and sewage services within a single country, which is concurrent with other literature reviews of water sector benchmarking (Abbott and Cohen, 2009; Worthington, 2014). One of the few articles that have investigated cross-boundary performance is De Witte and Marques (2010a) who investigated drinking water company performance across Netherlands, England and Wales, Australia, Portugal, and Belgium, and found that benchmarking incentive schemes have a significant positive impact on efficiency. Other examples include Ferro *et al*. (2011) who focussed on Latina America and See (2015) who assessed a sample of 40 public water utilities across Southeast Asia. Berg and Marques (2011) and Cetrulo *et al*. (2019) highlight a further gap in the literature, based around the limited quantity of research incorporating quality indicators in developing countries. Chapter 6 addresses the lack of cross-border water sector benchmarking and specifically focusses on wastewater treatment quality as both a control of the core sample and a part of the analysis.

It is apparent that there are various gaps and inconclusive topics still present, as outlined above, despite the ever-increasing number of publications, which was calculated to be 4.94% per year during 2000-2019 in a sample of 142 (Goh and See, 2021). Another gap appears to be the study of GHG emissions from the water sector across regions (Goh and See, 2021). This is important information as it could inform targeted approaches to reduce emissions and increase their accuracy. Chapter 6 includes this within part of its study, finding that the balance between wastewater treatment quality and GHG emissions is crucial, particularly in countries with carbon intense electricity grids. As well as the gaps emphasised, the nature of benchmarking, as noted in Section 2.1, is an iterative and constant process, meaning there is value in producing up-to-date analyses on performance. This ensures companies are always improving, regulation can be fair and accurate, and future research can build upon it. These aspects are particularly relevant as Goh and See (2021) comment that performance analysis research across the water and sewage industry is still immature.

2.3. The UK water sector

The UK water industry was highly fragmented in the 20th century, exemplified by the fact that in 1945, there were more than 1,000 organisations involved in supplying water and over 1,400 concerned with sewage disposal (OFWAT, 2020a). The focus was to consolidate local authority undertakings and extend services to rural communities. The Water Resources Act 1963 was later introduced and acknowledged the importance of a co-ordinated approach to water resource planning, introducing an administration system for abstraction permits. In the late 1960s and early 1970s water resource planning problems continued though, which along with forecasts of higher future demand, caused a restructuring of the industry, culminating in the Water Act 1973. The act created ten regional water authorities, each covering a river basin responsible for water supply, quality and sanitation in the region. The Act required the authorities to operate on a cost recovery basis, with capital raised by borrowing from central government and revenue from services, leading to central government setting performance aims. This was the beginning of efficiency measurement within the water industry, with a focus on the financial aspects of the industry, specifically production and cost (Ofwat, 2006).

The period that followed was marked by insufficient expenditure and investment on key capital maintenance due to rigid fiscal controls from central government, stemming from debt inherited by the water authorities and general economic instability (Hutton, 2020). This caused problems, particularly evident in the 1980s under the conditions of the more stringent European legislation and elevated environmental awareness of the public (Environment Agency, 2019). The government’s response culminated in the Water Act 1983, which reduced local government decision making and gave scope to access private capital markets. Despite the change, a significant number of pollution incidents continued as capital investment was still lacking (OFWAT, 2006). As other public services became privatised and the water sector continued to be under-invested due to regional water authorities having an inability to borrow from central government, the government concluded that privatisation was the optimal outcome, fulfilling the Conservative government's desire to privatise the water industry following privatising proposals in 1984 and 1986 (Lobina and Hall, 2001). The UK water industry was privatised in 1989 and the assets of the ten regional water authorities were all transferred into limited companies. To ensure sufficient investment to appease increasingly strict European environment legislation on river, bathing, coastal, and drinking water quality, and confront the existing backlog in infrastructure maintenance, the government wrote off £5 billion of the industry's debt and gave a further £1.6 billion (Robson and Howsam, 2006). Further capital was raised by floating the companies on the London Stock Exchange and via the provision of capital tax allowances. To safeguard the interests of the environment and customers, the roles of regulation and provision were divided into three separate independent bodies: the Drinking Water Inspectorate, the National Rivers Authority (now the Environment Agency), and the Office of Water Services (OFWAT) (OFWAT, 2020a).

The water sector in England and Wales is currently made up of 25 private companies, split up into 11 WaSCs, 9 WoCs, and 6 local water companies delivering a mixture of services (Figure 2.2), while Scottish Water and Northern Ireland Water provide the delivery of high-quality drinking water and collect and treat wastewater in the rest of the UK. To ensure levels of service and quality remain high and to maintain efficiency within a monopolised environment with little competition, the regulatory framework for the sector is diverse and extensive. The overall water and sewage policy framework, covering standards setting, drafting legislation, and creating special permits, is undertaken by the Department for Environment, Food and Rural Affairs in England, and national governments in the rest of the UK (OFWAT, 2020a). The environmental regulators in England, Scotland, and Northern Ireland are the national

Environment Agencies, whereas Natural Resources Wales fulfils that role in Wales. The function of the environmental regulators is to ensure that the natural resources utilised by water companies are sustainably maintained, enhanced, and used, now and in the future, which amongst other actions, includes reducing flood risk, promoting sustainable development, and securing environmental and social benefits (Natural Resources Wales, 2021). Further assistance and practical advice on safeguarding nature is provided by Natural England, who have a particular focus on promoting natural benefits for society. To make sure drinking water quality is safe and meets water quality standards, the Drinking Water Inspectorate and Drinking Water Regulator for Scotland regulate companies by frequently inspecting individual companies and checking the water quality tests that water companies carry out (Water UK, 2017). The customers have a specific body representing them too, in the form of the Consumer Council for Water (2021), who monitor customer satisfaction and investigate complaints that have not been satisfactorily resolved.

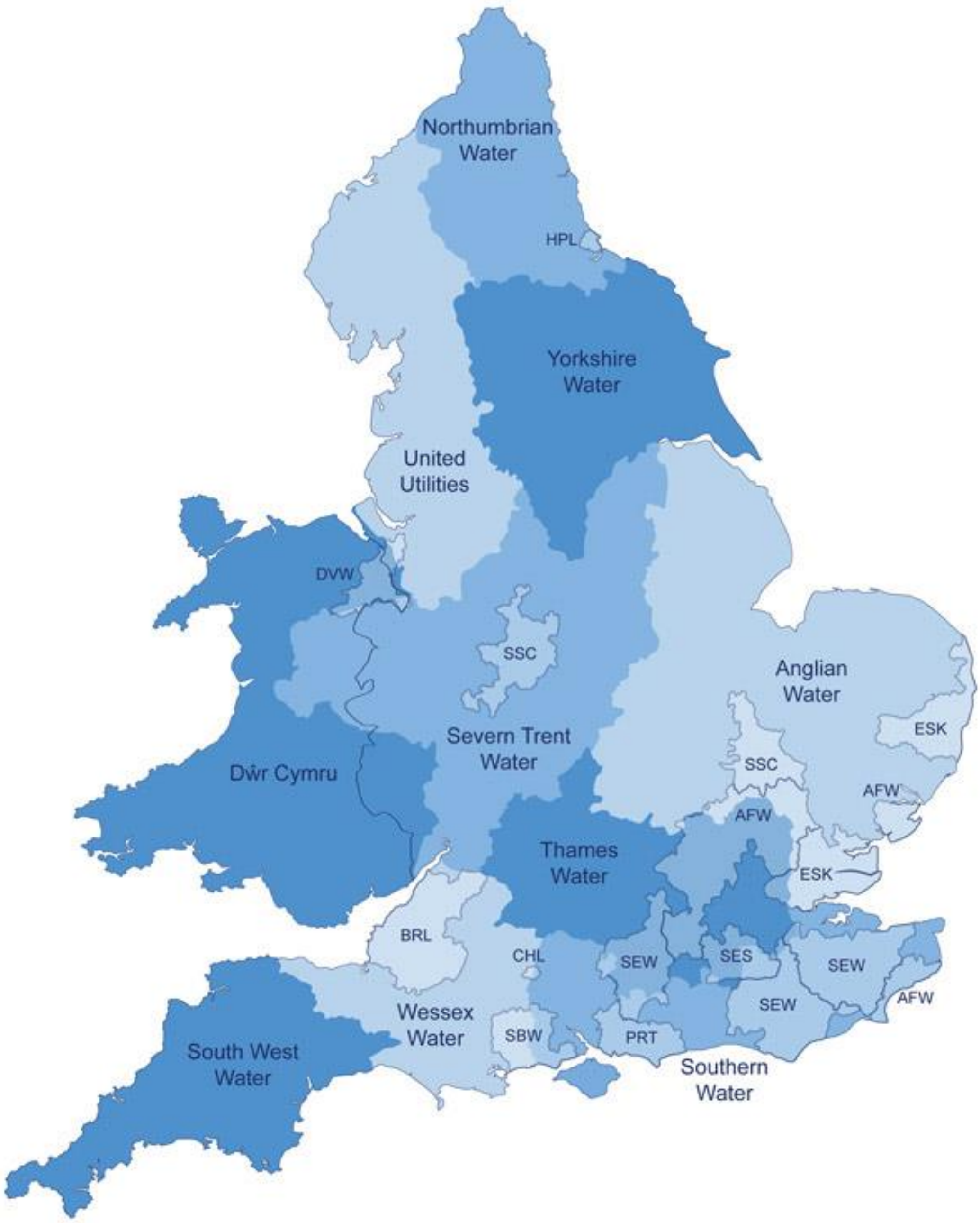

Figure 2.2. *Territorial map of water companies in England and Wales (OFWAT, 2021).*

One of the most important regulators is the economic regulator OFWAT, who along with the Water Industry Commission for Scotland, and Utility Regulator in Northern Ireland, promote competition, ensure companies can carry out their functions now and in the future, whilst also promoting efficiency (Council for Science and Technology, 2009). In an environment without market competition, the regulator has a vital role to control prices, protect customer interests, and ensure adequate investment, which is why evaluating efficiency on water companies and essentially ensuring regulation is working affectively is so important. One of the tools they use is to set price limits, achieved via price reviews conducted every five years, the latest one being PR19 (OFWAT, 2020b). The reviews take place by each company submitting a business plan for the following five years, which is then assessed by the economic regulator. OFWAT's regulatory mechanism of the price-cap is then applied, which is RPI + k, RPI being the retail price index and k being the adjustment element, referring to the performance, efficiency, and service of the companies. OFWAT (2020) declare that collectively, this framework of regulation has enabled UK water companies to invest more than £130 billion to maintain and improve services and assets. However, Yearwood (2018) claims that this investment has not all been for assets. The 40% increase in water bills since 1991 was supposed to be due to these high capital investments required, but Yearwood (2018) shows that it is a result of high interest payments on £47 billion of debt, accrued from £50 billion paid in dividends to shareholders. The companies could have funded their operations and investments from customer bills alone, without taking on debt. Part of the 'k' element and the performance assessment by OFWAT and other regulatory bodies is conducted through benchmarking, which is essential in the monopoly environment of water utilities, where firms do not compete against each other and consumers cannot leave. This is mostly achieved using normalised KPIs, however, for complex systems with numerous goals and multiple inputs and outputs, more sophisticated approaches are often required. Being able to advance these benchmarking techniques clearly has value in improving regulation, and therefore benefiting consumers, in addition to water managers, policy makers, and academia.

2.4. Summary

The literature reviewed in Section 2 emphasises various potential knowledge gaps to be filled and areas where advancements can be made. Foremost, methodologies to accurately capture the complex systems of water companies are increasingly important and sought after. There are many methodologies that have been tested and the most popular is data envelopment analysis however, it does have limitations. Iterations to this popular method have been developed and it is highly valuable to test them in order to add to the evidence base for future application. Progressing methodologies is beneficial to the water sector and the wider community of benchmarking and performance analysis. In addition, it is clear that benchmarking is an iterative process that requires constant application for the tool to have maximum effectiveness. By continuing this process without overlapping too much with other studies, real value can be contributed both now and in the future through up-to-date data collection and the efficiency results themselves. A further aspect of water utility benchmarking which can enhanced is the key performance indicator use to represent sustainability, which manifests within key goals now in many countries and specifically in the UK water sector. Frequently social and environmental indicators are lacking from analyses however, their importance is highlighted in regulation and company outputs. By filling these literature gaps and advancing the knowledge base, assistance can be provided to benchmarking and performance analysis towards it becoming a mature research field, which can enable decision-making to be more informed, whether that is by regulators, water managers, policy makers, or academics, ultimately benefiting everyone including the planet and customers.

3. Economic and environmental efficiency of UK and Ireland water companies: Influence of exogenous factors and rurality

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Andrew Norton: Conceptualization, Methodology, Formal analysis, Writing – original draft. Only for the early work on Section 3.3.5 – rurality influence on efficiency.

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Abstract

For water companies, benchmarking their performance relative to other companies can be an effective way to identify the scope for efficiency gains to be made through infrastructure investment and operational improvements. However, a key limitation to benchmarking is the confounding effect of exogenous factors, which may not be factored in to benchmarking methodologies. The purpose of this study was to provide an unbiased comparison of efficiency across a sample of water and sewage companies, accounting for important exogenous factors. Bias-corrected economic and environmental efficiency estimates with explanatory factors were evaluated for a sample of 13 water and sewage companies in the UK and Ireland, using a double-bootstrap data envelopment analysis (DEA) approach. Bias correction for economic and environmental efficiency changed the rankings of nine and eight companies, respectively. On average, companies could reduce economic inputs by 19% and carbon outputs by 16% if they performed at the efficiency frontier. Variables explaining efficiency were: source of water, leakage rate, per capita consumption and population density. Population density showed statistical significance with both economic (p-value 0.002) and environmental (p-value 0.001) efficiency. Consequently, a rurality factor was defined for each company's operational area, which was then regressed against normalised water company performance data. More rural water companies spend more per property (R^2 of 0.633), in part reflecting a larger number of smaller sewage treatment works serving rural populations (R^2 of 0.823). These findings provide new insight into methods for benchmarking, and factors affecting, water company efficiency, pertinent for both regulators and water companies.

Key words: Data Envelopment Analysis, Double-Bootstrap, Water Utilities, Performance Analysis, Explanatory Factors, Urbanity

3.1. Introduction

The water and sewage industry has fundamental links to all aspects of sustainability, those being economic, social and environmental considerations. This is through the sector being responsible for delivering potable water, a social necessity, which requires significant amounts of energy, physical infrastructure (treatment plants and pipes) and financial inputs to purify, distribute, and treat before and after usage to protect receiving waters and uphold sanitary standards (Olsson, 2015; Saleh and Gupta, 2016). Increasing economic and environmental efficiency reduces the consumption of resources and could enable a more reliable service, in line with industry, consumer and societal interests. Benchmarking is regarded as a valuable tool for increasing efficiency because it can be used to evaluate the comparative performance of companies, underpinning effective regulation. Examples where benchmarking is used by regulators arise in many different countries, such as England and Wales via Office of Water Services (OFWAT), Portugal by Entidade Reguladora dos Serviços de Águas e Resíduos (ERSAR) and Latin America via Regulación de Agua y Saneamiento en las Américas (ADERASA) (Berg, 2013), to name just a few. Even where regulators do not employ benchmarking, companies are taking it up themselves to help them perform competitively against sector leaders and to enable innovation collaborations for best practices. This is evidenced by voluntary subscriptions to organisations such as the EU Benchmarking Co-operation, South East Asia Water Utility Network (SEAWUN), and the International Benchmarking Network (IBNET), which compare key indicators from water utilities across international boundaries (Asian Development Bank, 2018; IBNET, 2018).

Benchmarking is also a topic of interest in academia. Frequent attempts have been made to refine and optimise benchmarking methodologies for the water sector as well as to validate new techniques (Daraio and Simar, 2006; Berg, 2013) and provide evidence on factors that influence efficiency (De Witte and Marques, 2010b; Lannier and Porcher, 2013; Marques *et al.*, 2014). The most popular type of method for conducting benchmarking in the literature is production frontier analysis (Berg, 2013). A production frontier can be calculated with parametric methods (Kumbhakar and Lovell, 2004) or non-parametric methods such as data envelopment analysis (DEA), which is the most popular of the production frontier methods (Song *et al*., 2012). The reason for the popularity of DEA is that is has three fundamental characteristics, which make it beneficial for assessing water and sewerage companies (WaSCs). 1) It integrates multiple inputs and outputs for each unit, providing a multi-criteria analysis; 2) weightings applied to aggregate inputs and outputs are generated endogenously; and 3) it does not require a priori assumptions about the functional relationship between the inputs and outputs (Berg, 2013).

Despite the advantages that DEA offers, it has a crucial limitation in that it is a deterministic method, meaning statistical inferences cannot be drawn from conventional DEA efficiency scores (Simar and Wilson, 2007). This is of particular relevance for WaSCs, since DEA does not allow the use of regression analysis to evaluate the explanatory factors. Cazals *et al*. (2002) proposed a method to overcome this limitation, referred to as 'order-m', which is a partial frontier method that uses a portion of the original population sample to estimate the efficiency scores. Despite the advantages of the 'order-m' method in terms of enabling statistical evaluation of efficiency scores, it has drawbacks (Daraio and Simar, 2007). The limitations are specifically related to the selection of 'm', that is the sample taken from the original larger sample – the representativeness of this sample greatly affects the efficiency scores (Da Cruz and Marques, 2014).

An alternative approach is Simar and Wilson's (2007) double-bootstrap procedure, which allows for hypothesis-testing and statistical inferences in the DEA method, thus enabling the exploration of determinants of efficiency, whilst also bias-correcting the efficiency scores yielded from the DEA model (Yang and Zhang, 2018). As Gomez *et al*. (2017) note, the advantages of the bootstrap method have led to its application in an array of different areas, such as banking (Tziogkidis *et al*., 2018) and educational institutions (Andersson *et al*., 2017), as well as water companies (De Witte and Marques, 2010c; Ananda, 2014). However, the double-bootstrap DEA method has not been used extensively on water and sewage companies previously, with only one study (Molinos-Senante *et al*., 2018a) to the best of our knowledge having done so.

Many research papers have assessed explanatory factors for the reasons behind the performance of their analysed water utilities and networks, with Conti (2005) highlighting the "role played by environmental variables in 'shaping' both the technology and the efficiency levels of the water utility industry". Examples include, but are not limited to ownership, size, technology use, energy consumption, source of water, year of construction, peak factor, and particularly relevant to this study population density (Abbott and Cohen, 2009; Guerrini *et al*., 2011; Molinos-Senante, *et al*., 2014a; Molinos-Senante and Guzmán, 2018; Peda, *et al*., 2013; Renzetti and Dupont, 2009).

Despite there being a diverse range of exogenous factors evaluated in performance assessments of water utilities, "rurality" is a potentially pertinent differentiating factor that is rarely explored. De Witte and Marques (2010a) documented just eight academic studies prior to their 2010 publication that included customer or population density (a proxy for rurality), as an explanatory factor. Aside from those eight, there have been very few following this. A few notable studies are Carvalho and Marques (2011), Lannier and Porcher (2013), and Marques *et al*. (2014). Since population density is only a crude partial indicator if used to assess the influence of rurality/urbanity, a different approach is needed. There is, however, very little literature available discussing methodologies for assessing or clustering the catchments for water authorities, especially in terms of rural/urban split. Perhaps most relevant work with regard to quantifying geographic situation is Neunteufel (2017), where the use of urban classifications to aid management decisions is used. This study highlighted how leakage rate should be perceived differently in terms of acceptable performance when considering the age of piping. The analysis was conducted via a clustering exercise, with prescribed boundaries to classify between rural, urban and metropolitan (described as "Urbanity" cluster).

The reason rurality is of interest is that without accounting for it in efficiency analysis and benchmarking, it limits avenues for improvement and it may appear that companies which operate more rurally than others are performing poorly. This has relevance for all performance across water only companies (WoCs) and WaSCs operating at varying scales of urbanity furthermore, it may be relevant to regulators when evaluating whether companies are doing enough to be efficient.

There were three objectives to this study, which are discussed in order throughout the upcoming sections. Firstly, bias-corrected comparison of economic and environmental efficiency scores across UK and Irish WaSCs. Secondly, identification of key factors that may affect bias-corrected efficiency scores. Thirdly, development of a framework to assess the influence of rurality on operational efficiency across a set of English and Welsh WoCs and WaSCs. Collectively, these objectives provide novel insight for the water services industry and contribute to the academic literature on benchmarking by displaying alternative methodologies, contributing bias-corrected results and analysis of factors affecting economic and environmental efficiency across the UK and Ireland.

3.2. Methodology

3.2.1. Efficiency estimate

To estimate the economic and carbon efficiency of UK and Irish water and sewage companies as well as the factors affecting their efficiencies, Simar and Wilson’s (2007) double-bootstrap DEA model with a truncated bootstrapped regression was used. This approach enabled bias-corrected efficiencies to be obtained, and facilitated an assessment of the variables that influence these efficiencies. The wider advantages of this method have already been mentioned above.

3.2.1.1. Sample and data description for efficiency estimate

The sample for the economic efficiency analysis consisted of 13 WaSCs in the UK and Ireland, whilst the environmental carbon analysis consisted of 12 WaSCs in the UK alone. The reported efficiency parameters were for the period April 2014 to April 2015. When applying a

DEA model, the sample should be as homogenous as possible; companies in this sample were all of similar size and conduct comparable operations. The source of the data was largely from Water UK (2015), a national organisation that represents and works with WaSCs throughout the UK, collating key UK water utility data from annual company reports. For data points that were missing from the Water UK set, alternative sources were accessed and are outlined as follows. Wastewater treatment volumes were largely sourced from 2017/18 data sets due to poor data availability for 2014/15; inter-annual variance in wastewater treatment volume is not significant (only 0.4% average year on year variance expected in the next 8 years according to the PR19 OFWAT data tables, data not shown). The wastewater data source for UK companies was OFWAT and their PR19 data tables (OFWAT, 2018a). For Irish Water, it was their business plan document (Irish Water, 2015a) which provided the majority of their data except *operational expenditure* (*OPEX*) which came from a 2015 financial statements document (Irish Water, 2015b) and wastewater compliance information, which came from a wastewater treatment report by the Irish Environmental Protection Agency (2016). For Scottish Water, water delivered, and per capita consumption data were recovered from a report from the Water Industry Commission for Scotland (2015), whilst their *OPEX* data were sourced from one of their own asset reports (Scottish Water, 2015). *OPEX* data were also acquired for Northern Ireland Water through an annual report (Northern Ireland Water, 2015). Finally, the percentage of abstracted water coming from surface water for all UK companies was obtained via direct correspondence with the British Geological Survey (M Ascott 2018, personal communication, 19 September).

The number of units (WaSCs) available for analysis in the DEA models was small relative to most studies on water utilities, and for a DEA model to avoid relative efficiency discrimination problems; the sample needs to meet a minimum size threshold. To determine a size thresholds that avoids discrimination problems, 'Cooper's rule' was used here, which states the number of units to be analysed must be ≥ max$\{m\ x\ s; 3(m+s)\}$ where m is the number of inputs and s is the number of outputs used in the model (Cooper *et al*., 2007). Since the samples used in this paper were 13 and 12, and both the economic and environmental assessments use two inputs and one output, 'Cooper's rule' was met. Furthermore, Molinos-Senante *et al*. (2018a) comments that utilising DEA with a bootstrap procedure ensured more accurate efficiency scores with a limited sample size.

The selection of representative inputs and outputs is imperative for a DEA model to produce valid results. The two inputs used in the economic model were *OPEX* and *capital expenditure* (*CAPEX*) as these accurately represent the key aspects of financial operations within a water company. *OPEX* in this study was made up of both wholesale and retail expenditure and excludes exceptional items, depreciation and amortisation. *CAPEX* was used under the assumption that the companies in the sample contribute enough for it to be sufficient to maintain and renew the distribution network long-term. Since Ireland's currency is Euros, Irish Water's *OPEX* and *CAPEX* figures had to be converted to GBP for the analysis using the 2011-2015 average exchange rate of 0.814 (Statista, 2018). The two inputs used in the environmental model are operational greenhouse gas (carbon dioxide equivalent) emissions and kilometres of water mains and sewage piping, which represents embedded emissions within capital assets. The length of sewage and delivery network provide a suitable proxy for embedded carbon emissions within a company given the dominance of this infrastructure in terms of material inputs. Greenhouse gas emissions, to the authors' knowledge, has not been assessed with the DEA method within the water utility literature. However; many studies have used length of piping as a proxy to represent financial capital (Mbuvi *et al*., 2012; Ananda, 2014; See, 2015; Molinos-Senante *et al*., 2018a) and fixed assets have been used to estimate carbon in other DEA literature (Zhu, 2018).

One output was used for both the environmental and economic efficiency analyses. This output is a combined volume of both *water delivered and wastewater treated* and combines the two key determinants of resource use within water utilities, reflecting the most common outputs used in the DEA water utility literature (De Witte and Marques, 2010b, Guerrini *et al*., 2013). The water delivered volumes were estimated from subtracting leakage rates away from distribution input, which is the amount of water entering the distribution system at the point of production. The wastewater treated volumes encompass all water treated at treatment plants, not just effluent from businesses and homes.

A fundamental driver of resource use within WaSCs is the quality of water they produce and the wastewater they dispose of (Plappally and Lienhard, 2012; Maziotis *et al*., 2015). With this in mind, companies should not be penalised in terms of efficiency assessment for producing higher quality outputs than others; therefore, this study follows Saal *et al*. (2007) and Molinos-Senante *et al*. (2015b) and adjusts the two indicators used to calculate net output according to available water quality parameters. Water delivered was corrected by the quality of the water (y_1) and wastewater treated was adjusted based on wastewater discharge permit compliance (y_2). A more accurate representation on quality could be achieved by understanding the raw water quality being treated for drinking water and knowing the quantity of pollutants (e.g., kg of BOD) removed however, in the absence of this data, the quality of drinking water (relative to UK legislative standards) and discharge permit compliance were used. The quality indicators are reported as percentages, with 100% meaning that all legal requirements are met. For this study, they are converted to decimals and are used as multipliers for the original output data, defined thus:

$$y_1 = WD \times DWQ \tag{3.1}$$

$$y_2 = WWT \times DPC \tag{3.2}$$

Where y_1 is the quality-adjusted water delivered; WD is the volume of drinking water delivered to customers; DWQ is drinking water quality; y_2 is the quality-adjusted wastewater volume treated; WWT is the wastewater treated volume; DPC is discharge permit compliance, an appropriate wastewater discharge quality proxy. The resulting figures for the indicators y_1 and y_2 then made up the solo output of both the environmental and economic DEA analysis.

In an attempt to decipher the reasons behind companies performing the way that they do, *population density*, *percentage of abstracted water being from surface water*, *leakage* and *consumption per capita* were used as the determinant variables to evaluate. These were selected as the most likely determinants of efficiency available from the aforementioned data sources, based on results of previous studies summarised above (De Witte and Marques, 2010a; Carvalho and Marques, 2011; Marques *et al*., 2014; Molinos-Senante *et al*., 2018a). The variables used for analysing the determinants of efficiency along with the inputs, outputs and quality variables used to determine the efficiency scores are summarised in Table 3.1.

Table 3.1. *Data sample description for use in DEA analyses, representing water supply and wastewater treatment.*

		Average	SD	Minimum	Maximum
Inputs	Operational expenditure (million£)	400	207	165	824
	Capital expenditure (million£)	447	328	156	1322
	Operational GHG emissions ($KtCO_2e$)	365	186	148	824
	Length of mains and sewage pipes (km)	82,460	39,081	30,961	139,880
Outputs	Water delivered & wastewater treated (ML/ day)	2556	1587	739	6338
Quality Variables	Drinking water quality (%)	99.9	0.1	99.5	100
	Discharge permit compliance (%)	97.2	4.7	83	99.9
Explanatory Variables	Consumption per capita (l/h/d) (excluding leakage)	139	16	115	181
	Population density (Population/km^2)	67	17	42	106
	Leakage (%)	24	9	12	49
	Surface water (%)	72	27	12	100

3.2.1.2. Standard DEA model

The DEA method was originally produced by Farrell (1957) and later developed by Charnes *et al*. (1978), and has since been frequently used to assess a vast array of water utilities (Berg, 2013). It is a non-parametric technique that employs linear programming to facilitate the creation of the efficient production frontier. The frontier develops the relative efficiency of the sample of decision-making units (DMUs), which in this case are the UK and Ireland water utilities, by comparing their inputs and outputs in relation one and other within the sample (Charnes *et al*., 1978). The technical efficiency of each DMU is then gauged by evaluating how far it is away from the frontier.

The model of the DEA method can orientate towards either inputs or outputs. Generally, water and sewage companies do not have much control over the quantity of their outputs, those largely being determined by demand for drinking water and sewage treatment. They do however have a large influence over their inputs, with a goal to reduce the resources going into them as much as possible, whilst still producing those outputs at the same standard; therefore, this study employed an input-orientated model. This is in line with similar literature that analyses water utilities with DEA methods (De Witte and Marques, 2010a; Berg, 2013). Furthermore, the model was based on varying returns to scale (VRS), which allows for scale effects. This is a reasonable assumption to make since the WaSCs being assessed are of various sizes and are likely to produce differing level of outputs with same level of inputs, which again, is concurrent with the majority of the literature (Berg and Marques, 2011; Peda *et al*., 2013; Guerrini *et al*., 2015; See, 2015).

Given j = 1, 2…, N units, each one using a vector of M inputs $x_j = (x_{1j}, x_{2j}, \ldots, x_{Mj})$ to produce a vector of S outputs $y_j = (y_{1j}, y_{2j}, \ldots, y_{Sj})$, the input-orientated DEA model is described as follows:

$$
\begin{aligned}
& Min\ \theta_j \\
& s.t. \\
& \textstyle\sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta x_{i0} && 1 \leq i \leq M \\
& \textstyle\sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{r0} && 1 \leq r \leq S \qquad (3.3) \\
& \lambda_j \geq 0 && 1 \leq j \leq N
\end{aligned}
$$

θ_j is a scalar whose value signifies the efficiency of the evaluated unit (WaSC), which is efficient when θ_j = 1 and inefficient when θ_j > 1. This subscribes to Shephard efficiency, as opposed to Farrell efficiency that has inefficient units as < 1; by following this variation, it removes the need to convert the efficiencies for the next methodology section. M is the number of inputs used, S is the number of outputs generated, N is the number of units assessed and

λ_j is a set of intensity variables that symbolise the weighting of each analysed unit j within the formation of the frontier.

3.2.1.3. Double-bootstrap DEA method

The literature on DEA shows Tobit regression as the most popular method to analyse the effects of explanatory variables on technical efficiency. It is a two-stage approach and works by regressing the sample of explanatory variables against the technical efficiency scores, originally acquired through a DEA model (Hoff, 2007). There are, however, limitations to this method, an example being: the DEA efficiency scores are found to be serially correlated, which causes results to be biased, then explanatory variables are caused to have errors due to being derived from those efficiency estimates (Simar and Wilson, 2007).

In order to estimate the technical efficiency of a sample with DEA but without bias, whilst also assessing the influence of explanatory variables, Simar and Wilson (2007) introduced a double-bootstrap model. This method operates by simulating the sample distribution by mimicking the data-generation process (Simões *et al*., 2010); in this study, 2,000 bootstrap samples were generated. The DEA efficiency scores are then re-estimated with the new generated data. The difference between the original scores and the estimated frontier from the double-bootstrap method shows the amount of bias that would have potentially skewed results using other methods.

Simar and Wilson’s (2007) double-bootstrap method is summarised in the proceeding steps: 1) apply the standard DEA method to estimate Shepherd’s efficiency score for the WaSCs; 2) conduct a truncated normal regression with maximum likelihood method, regressing the estimated efficiency scores that are greater than one against the explanatory factors; 3) obtain bootstrap samples from the truncated normal distribution of the efficiency estimates; 4) using the bootstrap results, calculate the bias-corrected efficiency scores; 5) re-estimate the marginal effects of the explanatory factors with the bias-corrected efficiency scores in the second-stage regression; 6) apply a second bootstrap based on the empirical distribution on the second-stage bias-corrected regression; 7) for each explanatory factor attain 95%

confidence intervals. The full computational procedure referred to as algorithm 2 in Simar and Wilson (2007) is encapsulated below:

1. Estimate the DEA input-efficiency scores θ_j for all of the water and sewage companies in the sample by use of equation 3.3.
2. Carry out a truncated maximum likelihood estimation to regress θ against a set of explanatory variables z_j, $\theta_j = z_j\beta + \varepsilon_j$, and provide an estimate $\hat{\beta}$ of the coefficient vector β and estimate $\widehat{\sigma_\varepsilon}$ of σ_ε, the standard deviation of the residual errors ε_j.
3. For each company j (j = 1, …, N) repeat the following steps (3.1-3.4) B_1 times to obtain a set of B_1 bootstrap estimates $\widehat{(\theta_{jb})}$ for b = 1, …, B_1.

   3.1. Generate the residual error ε_j from the normal distribution N (0, $\widehat{\sigma_\varepsilon^2}$).

   3.2. Compute $\theta_j^* = z_j\hat{\beta} + \varepsilon_j$.

   3.3. Generate a pseudo set (x_j^*, y_j^*) where $x_j^* = x_j$ and $y_j^* = y_j(\frac{\theta_j}{\theta_j^*})$.

   3.4. Using the pseudo set (x_j^*, y_j^*) and equation 3.1, estimate pseudo efficiency estimates $\widehat{\theta_j^*}$.

4. Calculate the bias-corrected estimator $\widehat{\theta_j}$ for each water and sewage company j ($j = 1, \ldots, N$) using the bootstrap estimator or the bias $\widehat{b_j}$ where $\widehat{\theta_j} = \theta_j - \widehat{b_j}$ and $\widehat{b_j} = (\frac{1}{B_1} \sum_{b=1}^{B_1} \widehat{\theta_{jb}^*}) - \theta_j$.
5. Use the truncated maximum likelihood estimation to regress $\widehat{\theta_j}$ on the explanatory variables z_j and provide an estimate $\widehat{\beta^*}$ for β and an estimate $\widehat{\sigma^*}$ for σ_ε.
6. Repeat the following three steps (6.1-6.3) B_2 times to obtain a set of B_2 pairs of bootstrap estimates $(\widehat{\beta_j^{**}})$, $(\widehat{\sigma_j^{**}})$ for $b = 1, \ldots, B_2$.

   6.1. Generate the residual error ε_j from the normal distribution N (0, $\widehat{\sigma^{*2}}$)

   6.2. Calculate $\widehat{\theta_j^{**}} = z_j\widehat{\beta^*} + \varepsilon_j$.

   6.3. Use truncated maximum likelihood estimation to regress $\widehat{\theta_j^{**}}$ on the explanatory variables z_j and provide as estimate $\widehat{\beta^{**}}$ for β and an estimate $\widehat{\sigma^{**}}$ for σ_ε.

7. Construct the estimated $(1-\alpha)\%$ confidence interval of the n-th element, β_n of the vector β, that is $[Lower_{an}, Upper_{an}]$ = $[\widehat{\beta_n^*} + \widehat{a_a}, \widehat{\beta_n^*} - \widehat{b_a}]$ with
$$Prob\left(-\widehat{b_a} \leq \widehat{\beta_n^{**}} - \widehat{\beta_n^*} \leq \widehat{a_a}\right) \approx 1-a$$

For solving the model, the statistical computing software ‘R’ with the package ‘rDEA’ developed by Simm and Besstremyannaya (2016) was used.

3.2.2. Analysing operational and rurality correlations

3.2.2.1. Water utility data description

So that water companies can benchmark themselves against each other in the UK, historic information about their operations, investment and performance is collated and shared. In the interests of transparency, this information is published by Water UK, in the same format in which it was submitted by companies at the end of the 2014/15 financial year and as reported to OFWAT. The data shared by Water UK in 2015 is the sole source for the information utilised in the rurality analysis. This information has not necessarily been through the assurance procedures and tests that would normally be applied to regulatory performance reporting data.

Including a mixture of WaSCs and WoCs within the sample could undermine the analysis due to their different operations and sizes. This issue is negated in the DEA analyses part of the study as just WaSCs were assessed. In order to minimise the impact of mixed operations and size in this part of the study, the data were normalised. Where data were reported as financial spend and total operation information by each water company, they were normalised against numbers of properties connected for that service. i.e. dividing total operation information and financial spend by the number of properties connected for water and/or sewage services as appropriate. Other already normalised data were left as originally provided. A refined version of this data is displayed below in Table 3.2 to provide a visual example; a full set of the data is available in supplementary information.

Table 3.2. *Refined indicator summary table used in rurality correlation analysis (M = million, S = sewage, GWP = Global Warming Potential, STWs = Sewage Treatment Works, 105a sewers = private lines that have become owned by water companies, size bands 1-3 = smallest group of treatment works).*

Indicator	Metric	Average	Standard deviation	Minimum	Maximum
Total company spend	£/property connected for sewage and water	206	79	90	373
Number of STWs	number/M property served S	353	240	61	905
Length of sewers (km)	m/properties connected S	14	1.4	11	17
Length of 105A sewers (km)	m/properties connected S	10	2	7	14
Load treated by all STWs	kg BOD5/day/M properties	135	44	60	177
Load treated by STWs in size bands 1-3	kg BOD5/day/M properties	6,335	4,737	1,062	15,459
Total Company GWP	kgCO_2e/property connected for water and sewage	155	47	117	273

3.2.2.2. Rurality factor assessment

Water company operating area boundaries are not made publicly available by regulating bodies such as the Environment Agency, Natural Resources Wales or Drinking Water Inspectorate, due to complex licencing issues. Water companies may provide geospatial data (*i.e.,* their supply boundary polygons) or maps outlining their operations at their discretion. Using published data sources (both geospatial and mapped outputs) combined with data provided in response to direct requests, the potable and wastewater operational area boundaries were georeferenced and digitised (where required) using ESRI ArcGIS 10.4 and assembled into an England and Wales coverage.

The Rural/Urban Classification is an official statistic used to distinguish rural and urban areas. The classification defines areas as rural if they are outside settlements with more than 10,000 resident population. The classification is then further divided via sparsity into whether the area is a small town, village, hamlet or conurbation of various extents (Office of National Statistics, 2013).

Geospatial data representing the 2011 Census Middle Layer Super Output Area (MLSOA) boundary polygons were obtained (in ESRI shapefile format) from the Office of National Statistics. The corresponding Rural–Urban Classification (RUC) identifiers for Small Area Geographies data were subsequently obtained in tabular form and joined using common attributes (the MLSOA identifier codes).

The water company operational area datasets for potable and wastewater treatment were separately geoprocessed using intersection with the RUC MLSOA polygons. The resulting intersected dataset related each water company supply area to its constituent rural and urban area polygons (Figure 3.1). The area measures for each of the resulting polygons were re-calculated to account for any splitting and resizing of individual entities resulting from the geoprocessing, and then aggregated to their individual classes nested within each water company area using a summary statistical process. The percentages of the constituent classes were then calculated (Table 3.3).

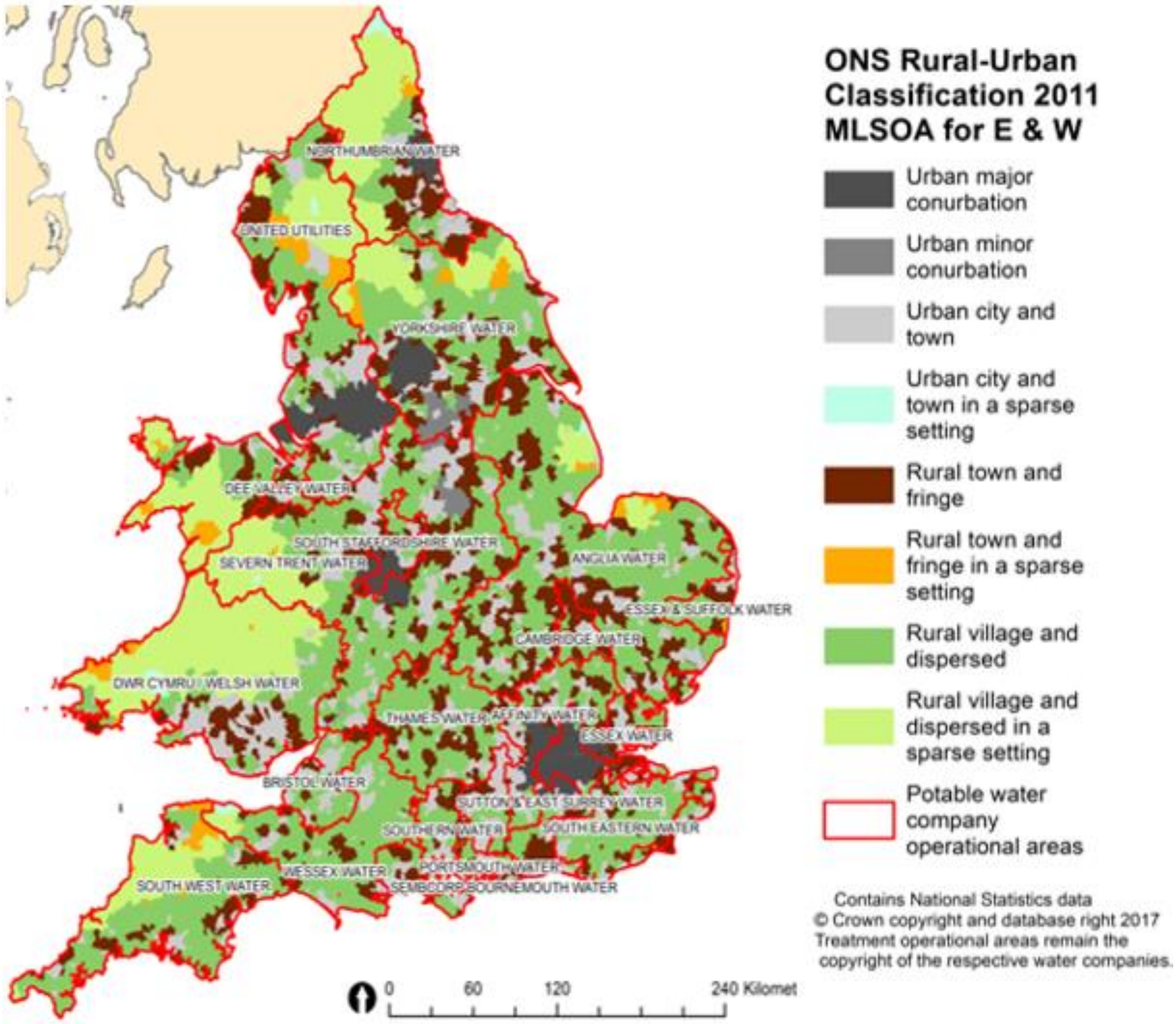

***Figure 3.1**. Catchment areas water supply companies in the England and Wales, showing the distribution of rural-urban classifications within them.*

Table 3.3. *The percentage of water and sewage supply areas of WaSCs and WoCs that fall into the primary classification of "rural".*

Water company	Water supply area: MLOSA rural-urban Index (% Rural)	Sewage supply area: MLOSA rural-urban Index (% Rural)	Total area classed as rural (%)
South West Water	91.5	91.7	91.6
Wessex Water	87.4	80.8	84.1
Welsh Water	86.9	86.2	86.6
Anglian Water	86.2	84	85.1
Essex & Suffolk Water	85.5		85.5
Cambridge Water	84.4		84.4
Northumbrian Water	81.3	81.2	81.3
Yorkshire Water	76.8	74.8	75.8
Severn Trent Water	75.6	75.2	75.4
Thames Water	71.8	60.6	66.6
United Utilities	69.2	69.3	69.3
South Eastern Water	69		69
Southern Water	68.7	71.8	70.3
Bristol Water	68		68
Bournemouth Water	64.2		64.2
Affinity Water	57.8		57.8
Portsmouth Water	55.1		55.1
South Staffordshire Water	49.1		49.1
Sutton & East Surrey Water	47.4		47.4
Essex Water	44.5		44.5
Dee Valley Water	32.2		32.2

3.2.2.3. Correlation methodological process

In order to evaluate if and how rurality affects water utility operations and therefore efficiency, regression analysis was undertaken. This was completed by calculating the R^2 value of the correlation between an operational parameter and the rurality percentage of the companies within the sample. The slope and intercept of the linier trendlines were also calculated to provide an average baseline from which to benchmark the performance of the utility companies assessed.

3.3. Results and Discussion

3.3.1. Economic efficiency estimate

The input-orientated Shepherd distance function that is subscribed to here regards efficiency scores higher than one as inefficient compared to the frontier, which are those operating at or closest to one. The initial DEA model, referred to in Figure 3.2 as 'non-bias corrected scores', estimated that seven of the 13 (53.8%) WaSCs are on the efficiency frontier and all have an efficiency estimate of one. This means that according this model, those seven companies cannot reduce their *CAPEX* and *OPEX* inputs, whilst also maintaining their *water delivered and wastewater treated* output levels. The mean efficiency was 1.140 with a standard deviation of 0.295. The implication is that an average WaSC can decrease their inputs by 12.3% (1-1/1.140) and still produce their outputs to the same standard, if they are to perform at the same level as the frontier or 'benchmark'. For a more detailed view of the specific efficiency scores, the rank changes, and the confidence intervals, see Supplementary Information.

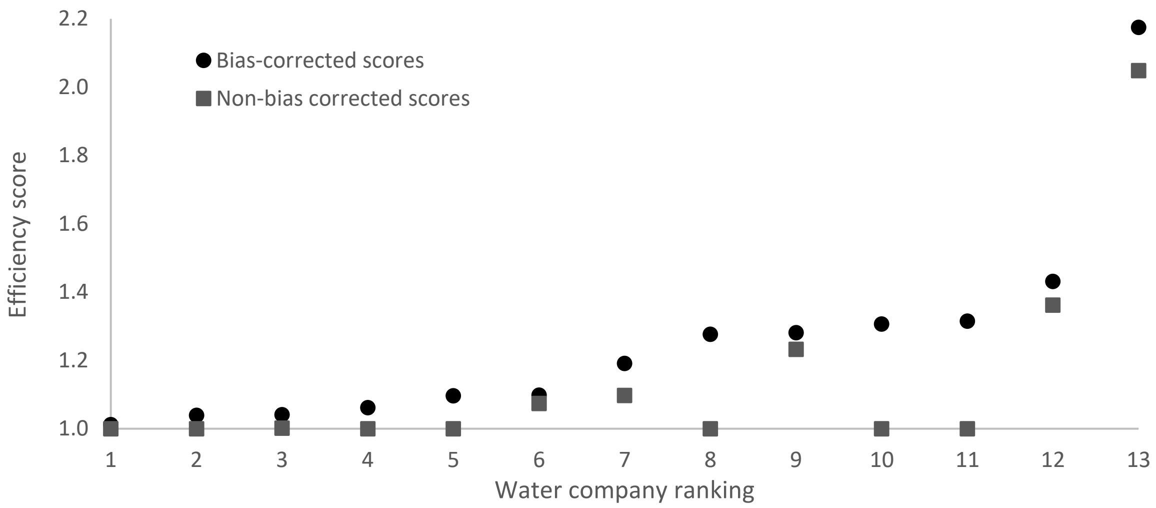

Figure 3.2. *Rankings based on biased standard DEA model and bias-corrected DEA estimates generated with 2,000 bootstrap iterations for the economic performance of 13 UK and Irish water and sewage companies.*

The bias for all WaSCs were zero or negative values, with mean average of bias being -0.116. This means the bias correction largely indicates that the sample are less efficient after bias-correction than in the original DEA model. This is concurrent with other studies (Ananda, 2014; See, 2015; Gomez *et al*., 2017; Molinos-Senante *et al*., 2018a) and the application of the technique (Simar and Wilson, 2007).

The mean average of the efficiency scores of the sample once bias was removed was 1.256. These analyses were repeated three times to prove validity and had an average difference of 0.22% (range -0.98%-1.29% between the repeats). This result indicated that on average if the water companies could perform at the benchmark level they could reduce their financial inputs by 19.4%, whilst still maintaining the same levels of service outputs. The range of the sample was large, with the most inefficient DMU having an efficiency score of 2.175, whilst the 12th most efficient company had a score of 1.431. This result displays that most of the companies were close to each other in terms of efficiency, which was expected as the UK has quite a mature water sector that has undergone benchmarking and regulation for decades. The result also shows that one company was significantly lagging behind its peers and could likely benefit from the sharing of best practise.

The average bias was -0.116 as noted above, which is a small efficiency correction overall, but it did have a significant impact on the rank of some WaSCs. For instance, DMU 1 climbed from rank eight to three. However, large bias corrections did not necessarily mean large changes in rank; for example, DMU 12 had the largest correction of -0.315, only moving it down from seven to 11. Collectively, nine of the 13 water utilities within the sample exhibited a rank change.

3.3.2. Determinants of economic efficiency

The key advantage of using the double-bootstrap methodology is that it enables a review of the determinants of the WaSC efficiency scores by applying a bootstrap truncated regression model. The explanatory factors assessed in this study were *consumption per capita*, *percentage surface water*, *leakage* and *population density*; their relationship with efficiency is displayed in Table 3.4. The bias-corrected coefficients with the method used in this study impact the efficiency of the water utilities negatively if the value is positive and have a positive effect on efficiency scores if the coefficient is negative. A p-value ≤ 0.05 displays that the explanatory variable is significant at the 95% significance level, essentially meaning the variable influences the efficiency estimates of the WaSCs.

Table 3.4. *Results of bootstrap truncated regression for economic efficiency analysis.*

Explanatory variable	Bias-corrected coefficients	Standard error	Low	High	P-Value
Consumption per capita	0.003	0.004	-0.006	0.010	0.527
Population density	-0.018	0.006	-0.032	-0.009	0.002*
Leakage	0.029	0.008	0.014	0.044	0.000*
Surface water %	-0.008	0.003	-0.014	-0.004	0.001*

*Note: *Statistically significant at the 1%, 5% and 10% levels.*

Percentage *surface water* abstracted had a significant positive relationship with efficiency (p-value 0.002). This result was unexpected and goes against what is found elsewhere in the literature. Carvalho and Marques (2011) observe mixed results, with a negative influence from *surface water* being observed when it makes up 70-80% and over 95% of a company's total abstraction, but a positive influence between 80-95% and no influence at all below 70%. Whilst recent studies that utilise a similar methodology to the one used in this study have found insignificant relationships with *surface water* (Marques *et al*., 2014; See, 2015; Molinos-Senante *et al*., 2018a), the expected results were that if a relationship was shown, it would be negative, such as that in Byrnes *et al*. (2010). The literature suggests that surface water requires purification of the water via chemical treatments that are more expensive than those used in groundwater treatment (Aubert and Reynaud, 2005; Shih *et al*., 2006). These costs are expected to be higher in surface water despite groundwater typically requiring pumping up to the surface, largely as a result of groundwater treatment mostly only being required for hardness and salinity (United States Geological Survey, 2016) and partially because some groundwater sources are from naturally occurring high pressure aquifers that flow to the surface without the need for pumping. It could be the case for UK and Irish companies the surface water they abstract is of a reasonably good quality and thus does not require much treatment and costs are lower.

The variable *consumption per capita* negatively influences the efficiency of the WaSCs to a non-significant level. Generally, the literature shows mixed results (Ananda, 2014; De Witte and Marques, 2010b; Marques *et al*., 2014). There is an argument that per capita consumption can affect efficiency scores positively due to links with economies of density (Byrnes *et al*., 2010; Carvalho *et al*., 2012). The indication is that once a distribution pipe network is set up, the amount of water actually running through it has minimal costs. The negative relationship found in this study may show that companies increase their efficiency via cost reductions as opposed to increasing the sale of water as noted by De Witte and Marques (2010a), however, the relationship found in this research is weak so any conclusions drawn from it are speculative (p-value 0.52).

As Table 3.4 illustrates, *leakage* is significantly negatively associated with efficiency. Logically, an increase in *leakage* should result in lower efficiencies since companies would have to extract, treat and pump more water to meet a specific demand. This result is concurrent with the overall trend in the literature (Corton and Berg, 2009; See, 2015; Molinos-Senante, 2018a). Despite this, *leakage* and its equivalent indicator, non-revenue water, are not always conclusive towards causing negative effects on efficiency. Marques *et al*. (2014) for example, concludes that *leakage* shows no influence on efficiency. Furthermore, Ananda (2014) and De Witte and Marques (2010a) show there is a relationship between increased *leakage* and increased efficiency.

Population density showed a significantly positive relationship with the WaSC efficiency scores. This result is consistent with the overwhelming theme of results from other empirical studies from various countries (Abbott *et al*., 2012; Guerrini *et al*., 2013; Marques *et al*., 2014; Ananda, 2014; See, 2015; Molinos-Senante *et al*., 2018a). The relationship between *population density* and efficiency is thought to be related to economy of densities (Byrnes *et al*., 2010; García-Sánchez, 2006). Essentially this means there is less network to install and maintain per population of customers, meaning fewer resource inputs per service output and therefore higher efficiency. Though these results concur with much of the literature, some studies still show up no significant relationship (Marques *et al*., 2014). *Population density* has particular relevance in this sample of UK and Ireland WaSCs. The water utilities compared operate in areas with a range of population densities, from 42 to 106 people/km^2, meaning certain companies have natural advantages or disadvantages in relation to each other. This should be taken into account when it comes to regulation and benchmarking to ensure fairer evaluations of performance. The un-level efficiency playing field created by *population density* has considerable implications for water company competitiveness and long-term viability, and is one of the key reasons that rurality/urbanity have been further investigated in this study (Section 3.3.5).

3.3.3. Environmental efficiency estimate

The results from the standard DEA model referred to in Figure 3.3 under 'non-bias corrected score', estimated that five of the 12 (41.6%) WaSCs are on the efficiency frontier and have an efficiency estimate of one. The mean efficiency was 1.096 with a standard deviation of 0.159. The average WaSC can decrease their carbon inputs by 8.8% (1-1/1.096) and still theoretically produce their water delivery and wastewater treatment outputs to the same standard, if they are to perform at the same level as their peers who operate at the frontier. As with Section 3.3.1, more information on efficiency scores is available in supplementary information.

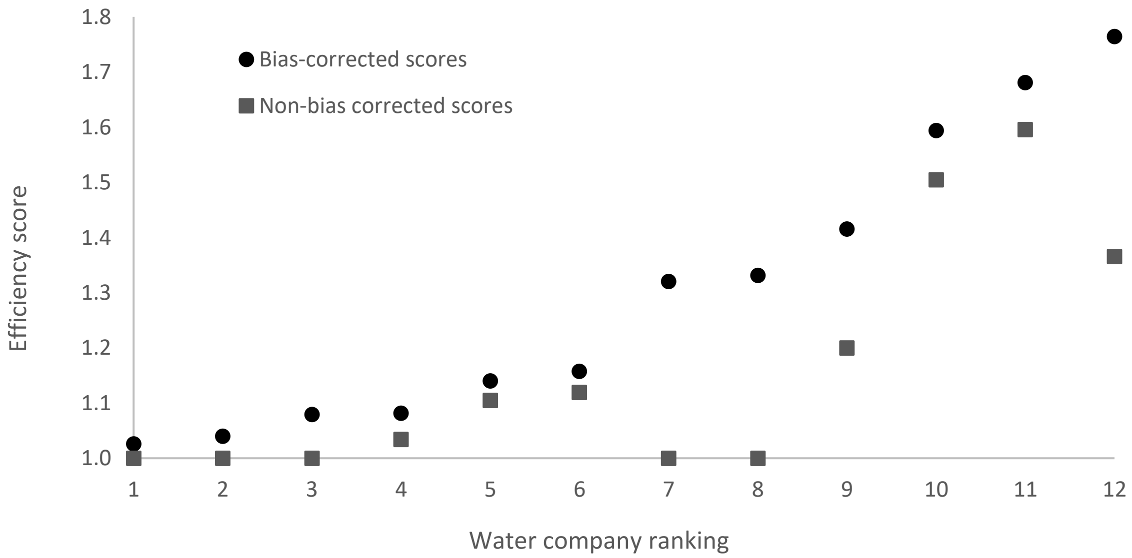

Figure 3.3. *Rankings based on biased standard DEA model and bias-corrected DEA estimates generated with 2,000 bootstrap iterations for the environmental performance of 12 UK water and sewage companies.*

The bias for all WaSCs were negative values, with -0.122 being the mean average of bias. As referred to in Section 3.3.1, the double-bootstrap DEA results were expected to display a drop in efficiency within the sample. Similar to the economic efficiency analysis above, the average bias was small but again it did affect how the companies were ranked. Eight out of 12 DMUs within this sample experienced a ranking change and in total, there was 15 ranking place movements even in this small sample.

The average environmental efficiency score once bias was removed was 1.219; this analysis was repeated three times and displayed an average difference of 0.22% (range -0.98%-1.29% between the repeats). The average corrected efficiency score means on average if the WaSCs could perform at the frontier, they could reduce their carbon inputs by 15.8%, whilst still maintaining the same levels of outputs. There were no significant outliers in efficiency however, the range from 1.026-1.765 combined with the clustering of the top four performing companies (1.026-1.082), indicated that a handful of companies are leading the way in terms of carbon efficiency, and could be exemplars for various best practice techniques.

3.3.4. Determinants of environmental efficiency estimate

The explanatory factors assessed in the carbon efficiency analysis were the same as those evaluated for economic efficiency, *consumption per capita*, *percentage surface water*, *leakage* and *population density*. As noted in Section 3.3.2, the bias-corrected coefficients for the explanatory variables (displayed in Table 3.5) are deemed to positively affect efficiency if their values are negative and adversely affect efficiency if their values are positive.

Table 3.5. *Results of bootstrap truncated regression for environmental efficiency analysis.*

Explanatory variable	Bias-corrected coefficients	Standard error	Low	High	P-Value
Consumption per capita	0.013	0.005	0.005	0.024	0.008*
Population density	-0.018	0.005	-0.030	-0.009	0.001*
Leakage	0.003	0.014	-0.024	0.031	0.867
Surface water %	-0.006	0.003	-0.012	-0.002	0.013*

*Note: *Statistically significant at the 1%, 5% and 10% levels.*

Consumption per capita was shown to significantly negatively influence carbon efficiency. This result matches the direction of effect on efficiency that was found in the economic analysis. The belief is that the more water each person consumes, the more treatment and energy is required, which are key sources of carbon. This relationship, like that in the economic analysis, is subject to economies of density, therefore it was not expected to necessarily show significance.

The percentage of *surface water* abstracted shows the same result as for the economic analysis, positively affecting efficiency to a significant degree. This is likely to be a result of lower electricity demand compared to groundwater pumping. Similar to the economic efficiency, the increased treatment usually reported for surface water may not be the case in the UK and Ireland, therefore there is a concurrent saving in carbon costs.

Population density, like *surface water* percentage, matched the results from the economic analysis. This was expected due to economies of density yielding naturally more efficient use of resources, as discussed in Section 3.3.2. More pumping is required if populations are spread over a large area, as well as more infrastructure such as piping and treatment works to support those populations, which have large amounts of embodied carbon within them.

The result for *leakage* however diverged between environmental and economic efficiency analyses, with a non-significant relationship shown for environmental efficiency. The anticipated result was that as *leakage* went up, so would carbon due to more pumping and therefore more energy being required. A possible cause of this result may be that capital projects into lowering *leakage* rates may have been carbon intensive, therefore the relationship over a one-year snapshot is not truly representative and companies who have not invested and thus have lower carbon emissions but higher *leakage* rates, appear to be performing better.

3.3.5. The role of rurality

3.3.5.1. Correlation results

Regression analysis was conducted on England and Wales water utilities, with a split of 10 WaSCs and 11 WoCs. The R^2 values closer to one indicate a stronger relationship between rurality and the displayed parameter. Table 3.6 displays the top regressions from the analysis; the total analysis results are available in supplementary information. The table displays the R^2 results, slope and intercept related to the parameter's relationship with rurality. The parameters contain data from varying areas including: economic costs, scale information, environmental performance and emissions, which are all normalised by properties connected. To make it easier to identify where a linear correlation is more likely, Table 3.6 has been sorted in terms of R^2 values.

Table 3.6*. Rurality relationship with economic cost, global warming potential, scale information, and environmental performance data divided by property connected for that service (M = million, S = Sewage, W = Water, GWP = Global Warming Potential, STWs = Sewage Treatment Works, size bands 1-3 = smallest group of treatment works).*

Indicator	Unit	R^2	Slope	Intercept
Number of sewage treatment works	number/M property served S	0.823	24.008	-1508.887
Total load treated by STWs in size bands 1-3	kg BOD5/day/M properties	0.792	-5.139	533.304
Total company spend	£/property connected for S&W	0.633	4.035	-69.813
Properties flooded in the year	other causes/M properties	0.544	-5.139	533.304
GWP of sewage treatment	kgCO_2e /property connected for sewage	0.508	0.880	-21.657
Total company GWP	kgCO_2e /property connected for water and sewage	0.485	3.890	-150.956
Spend on sewage treatment	£/property connected for S	0.471	1.632	-42.806
Sewage sub-total GWP	kgCO_2e /property connected for sewage	0.466	2.048	-68.807
GWP of sewage collection	kgCO_2e /property connected for sewage	0.460	1.041	-46.813
Water sub-total GWP	kgCO_2e /property connected for water	0.427	1.450	-17.841
Employee total	number/M properties connected W+S	0.407	8.620	717.109

The highest R^2 value from the economic data is for total company spend per property connected (0.633), indicating that as rurality percentage increases, so does the spending of the water companies. This direction of relationship is concurrent with the *population density* results from Section 3.3.2, although the strengths vary. This highlights how *population density* is a reasonable ‘crude’ indicator to use to gauge rurality/urbanity but other methods such as the one used here, may be more accurate.

Concerning scale information and assets one of the most striking correlations found in this study was that of rurality against number of sewage treatment works (STWs) with an R^2 of 0.823 for a linear trendline and 0.963 for an exponential one (shown in Figure 3.4). This was reflected in the largest correlated indicator within the environmental performance information, which is total load treated by STWs in size bands 1-3 (0.792), signifying that a large number of smaller size treatment plants are distributed across more rural areas. According to these results, dispersed small treatment works are the key driver behind rurality causing economic inefficiencies across water companies. This makes sense, as economies of scale are well documented for wastewater treatment in terms of infrastructure, maintenance, energy and chemical costs (Libralato *et al*., 2012). The correlations described above go some way in explaining the correlations found with economic factors against the percentage rural index, such as marginal correlations in spend on sewage treatment (0.471). Future research could evaluate solutions to this, for example, assessing whether it is more financially viable within certain areas to use more extensive piping and pumping networks to move the sewage to larger treatment plants.

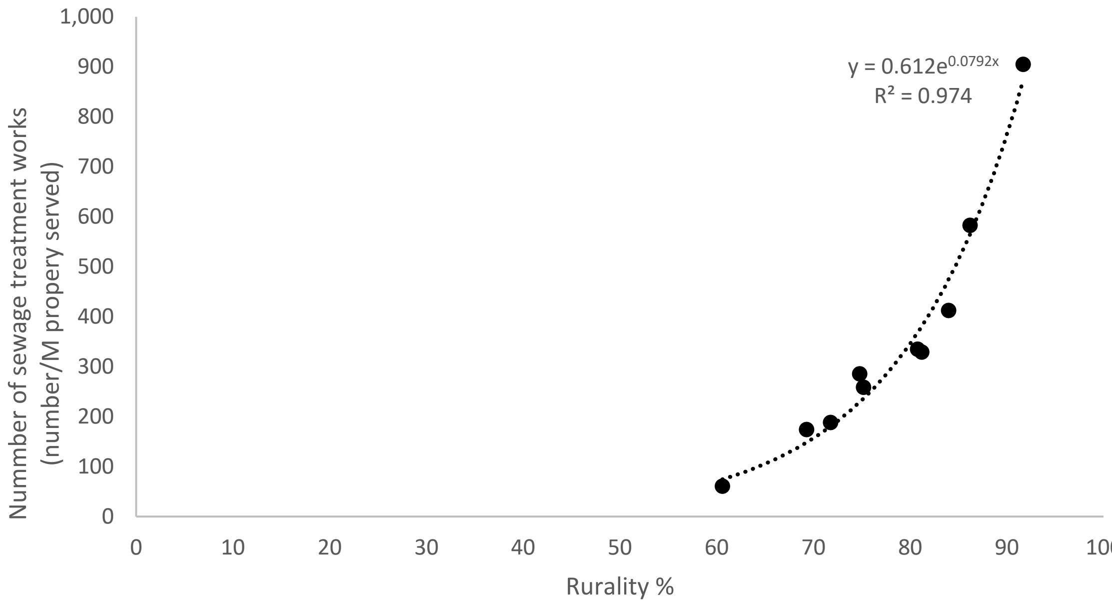

***Figure 3.4**. The correlation between percentage of catchment being rural and the number of sewage treatment works normalised by million properties served for sewage, with an exponential trendline.*

A more minor potential impact that rurality induces on companies appeared to be an increase in the number of employees (R^2 0.407). The number of employees may actually be at least partially a result of the increased number of sewage treatment works too; further emphasizing the impact of rurality appears to be largely resulting from dispersed wastewater treatment.

The R^2 results for emissions that display relationships were carbon equivalent of sewage treatment (0.508), total company carbon equivalent (0.485), sewage sub-total carbon equivalent (0.466), carbon equivalent of sewage collection (0.460) and water sub-total carbon equivalent (0.427). These trends concur with the economic regressions to a lesser extent, which further shows how rurality leads to inefficiencies, particularly within sewage operations. This effect of rurality on efficiency matches that of Gibson's (2017) who presented the effect of remoteness, measured in "travel time to significant city", and correlated this with a "water service provider performance index". Their research stated, "remoteness from a commercial centre clearly has a significant impact on performance".

Our results emphasise the important exogenous influence of rurality on water company efficiency, which needs to be taken into consideration when benchmarking. Doing so would enable companies to more accurately ascertain their scope for improvement, and to identify priority aspects to drive this improvement (e.g. by clarifying best practice). NGOs could use these techniques to more reliably evaluate best and worst performers within the sector, whilst regulators could define more rigorous performance targets for urban water companies and adjust targets for rural companies to account for exogenous factors.

3.3.5.2. Methodology appraisal

In terms of methodology, the framework presented here provides a powerful tool to benchmark among companies where exogenous factors may influence spend or performance. Our approach may be preferential to methods that use clustering of similar company attributes where a decision has to be made whether to include borderline data in one or another cluster, this method instead provides a “sliding scale” to make individual benchmark cases.

The same methodology was also applied to the operating catchments of one water authority, and similar trends where found, although with fewer data points. That exercise highlighted another use for the method within companies, in aiding a more holistic approach to regional budgeting or how operational areas are drawn, especially concerning sewage treatment and collection.

The influence of topography was also studied within one operation catchment by means of the Melton Ruggedness Number and a 3D Analyst 2D area; however, no notable correlation was found for that study. However, the influence of topography on water company efficiency may merit further investigation.

3.4. Conclusions

The aims of this paper were to utilise a double-bootstrap Data Envelopment Analysis (DEA) method to compare unbiased environmental and economic efficiency across water companies, and to explore factors influencing these efficiencies, including the specific role of rurality. There are four main conclusions to draw from this work. Firstly, the results show that the average company could reduce their economic inputs by 19.4% and carbon emissions by

15.8% by stepping up to the efficiency frontier. Thus, we demonstrate that there is considerable scope for improvement in economic and environmental efficiency across water companies if they adopt the practises of the top performers. Secondly, bias-correction of DEA results using the double-bootstrap method changed performance rankings for nine companies in the economic evaluation and eight companies in the environmental evaluation. We propose that such bias correction is vital to undertake accurate benchmarking across water companies. Thirdly, the study identified important factors influencing efficiency. *Surface water* sourcing was significantly positively associated with economic and environmental efficiency (p-values 0.001, 0.013) as was *population density* (p-values 0.002, 0.001). These exogenous factors are beyond the control of water companies, and thus need to be corrected for when benchmarking. Water *consumption per capita* displayed a negative association with environmental efficiency (p-value 0.008); whilst *leakage* rate showed a negative effect on economic efficiency (p-value (0.000). These factors are at least somewhat within the control of water companies, and should be prioritised to improve efficiency. The fourth conclusion of this study is that the degree of catchment rurality significantly influences the efficiency of water service companies. More rural catchments are associated with higher water company total spend and higher greenhouse gas emissions per property connected is (R^2 of 0.633 and 0.485). Operational data correlations suggest that this is a consequence of a greater number of smaller decentralised sewage treatment works in more rural areas (R^2 of 0.823 for number of treatment works, R^2 of 0.792 for small treatment works). It is clear that exogenous factors such as rurality play a significant role in determining the apparent efficiency of water service company operations, and thus benchmarking should be adjusted to reflect this non-level playing field. Future research and development supporting more efficient water services should focus on how to mitigate the resource burdens associated with larger numbers of smaller sewage treatment plants in rural areas.

4. Key performance indicators to explain energy & economic efficiency across water utilities, and identifying suitable proxies

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Abstract

Water companies consume up to 8% of global energy demand, at billions of dollars' cost. Benchmarking of performance between utilities can facilitate improvements in efficiency; however, inconsistencies in benchmarking practices may obscure pathways to improvement. The aspiration was to conduct an unbiased efficiency comparison within a sample of 17 water only companies and water and sewerage companies in England and Wales, accounting for exogenous factors, whilst evaluating the accuracy of common proxies. Proxies were tested, and bias-corrected energy and economic efficiency scores with explanatory factors were analysed using a double-bootstrap data envelopment method. Bias correction altered the rankings of two companies for energy efficiency only. Results imply that on average, companies could reduce energy inputs by 91.7%, and economic inputs by 92.3%, which was symptomatic of the companies specialising in drinking water supply considerably out-performing combined water and sewerage companies. As exogenous influences were likely to be a factor in the disparity between the companies, five indicators were evaluated. The results varied but of note were *average pumping head height*, which displayed a significant negative effect for energy efficiency, and *proportion of water passing through the largest four treatment works,* that exhibited a significant negative effect on economic efficiency. Within proxy performance, *population served for drinking water* was an adequate replacement for *volume of water produced*, with results matching the core variable apart from two companies changing rank in the economic analysis. Conversely, *length of water mains* performed poorly when replacing *capital expenditure*, implying companies were on average 12.6% more efficient, resulting in ten companies changing their rank and causing explanatory variables to contradict direction of influence and significance. The findings contribute new insights for benchmarking, including how different types of water companies perform under bias-correcting methods, the degree to which factors affect efficiency and how appropriate some proxies are.

Key words: Performance Evaluation; Water Companies; Data Envelopment Analysis; Double-Bootstrap; Proxies; Explanatory Factors

4.1. Introduction

The water industry is a significant user of energy resources; with water companies spending billions of dollars per annum to ensure a high standard of cleanliness, whilst also protecting the environment through treatment of wastewater (Sedlak, 2014). Significant energy and economic costs are incurred by pumping, mixing and purification for contaminants such as heavy metals and inorganic salts (Yang *et al.,* 2019). Other resources consumed for the treatment of water include a variety of chemicals including algicides, chlorine, sodium hydroxide, and aluminium sulphate for a plethora of applications such as reducing algal blooms, disinfection, balancing pH, and coagulation-flocculation (Saleh, 2017). Moreover, contamination of drinking water sources with nutrients, in particular phosphorous and nitrogen, combined with regulatory requirements around acceptable concentrations is leading to increasing energy and economic costs for treatment. Biological nutrient removal and chemical precipitation are typically used to remove these elements; however, alternative lower-cost and effective methods are being investigated (Kuriqi, 2014; Saleh and Gupta, 2016; Li *et al.,* 2019).

The US Environmental Protection Agency (EPA, 2018) reported that for many municipal governments, drinking water and wastewater plants are often their largest energy consumers, typically accounting for 30-40% of municipality energy consumption. The EPA estimated that 2% of total energy use within the US is actually a result of drinking and wastewater systems. The US is not a particular area of high consumption either; 3% of all UK energy use is expended on drinking and wastewater systems (Fletcher, 2018). In fact, it is likely that these countries have low energy consumption from their water utilities relative to the rest of the world (Olsson, 2015). The United Nations stated that approximately 8% of global primary energy supply is used to deliver and treat water (UN Water, 2014; UNESCO, 2014). As well as the economic cost associated with such energy demand, it is responsible for considerable emissions of greenhouse gases (GHG), with the US and UK emitting 40 and 5 million tonnes CO_2 per year through the water sector, respectively (McNabola *et al.,* 2014; EPA, 2018). The imperative to reduce energy consumption and GHG emissions is a major driver for water companies to increase their efficiency (DEFRA, 2016).

Increasing energy efficiency would benefit companies’ bottom line (profitability) and the climate, and enable a more reliable service, assuming that saved resources would at least partially be spent elsewhere such as on replacing leaky pipes or upgrading water treatment facilities. Benchmarking is viewed as a key mechanism to achieve improvements in efficiency by analysing performance, comparing results and identifying areas for improvement, and ultimately facilitating sharing of best practice (Alegre *et al.,* 2017). One of the most common methods in academic literature utilised to benchmark is production frontier analysis (Berg, 2013). A frontier can be computed with parametric methods like stochastic frontier analysis or non-parametric methods such as data envelopment analysis (DEA). DEA has three essential components that make it advantageous when evaluating water utilities. Firstly, the approach enables integration of numerous inputs and outputs for each company, providing a multi-criteria analysis. Secondly, weightings assigned to aggregate inputs and outputs are produced endogenously. Thirdly, DEA does not need *a priori* inferences regarding the functional exchange between the inputs and outputs (Cooper *et al.,* 2011).

To decipher variables that influence efficiency in water utilities, there are four key methodologies available for use in the second stage of analysis using DEA (Molinos-Senante and Guzmán, 2018). One method is to group the decision-making units (DMUs), which are water utility companies in this research, according to the explanatory variables and apply non-parametric statistical tests to verify if there are differences in the distribution of efficiency scores among groups of DMUs (Molinos-Senante *et al.,* 2014a). This can be undertaken via several hypothesis tests such as analysis of variance, Kolmogorov-Smirnov distribution test or the Mann-Whitney test. This method however, does not allow isolation of the influence of the explanatory variables on the efficiency scores and therefore means causality cannot be determined (Molinos-Senante *et al.*, 2018a). Secondly, a common approach is to conduct a regression analysis of the efficiency scores from the first stage results against the explanatory variables being investigated, the typical approach being the use of a Tobit regression analysis (Guerrini *et al.*, 2013; Guerrini *et al.*, 2015). However, conventional inference methods used in the second stage of the DEA method are based on efficiency values that are serially correlated; therefore, any inferences based on them may not be reliable (Daraio and Simar, 2007). The process is regarded to have shortcomings, with Simar and Wilson (2007) and Bădin *et al.* (2014) proving that if the variables used in the original efficiency model are regressed against explanatory factors, then the second-stage estimates are inconsistent and biased. Due to these biases, the third main second-stage method 'order-m' was developed by Cazals *et al.* (2002). Order-m is a partial frontier method that uses just a portion of the sample to determine the efficiency scores, and enables the inclusion of evaluating exogenous variables (Carvalho and Marques, 2011). The limitation to this method is in its uniqueness, by only taking a fraction of the original sample, it has issues around sample size requirements and the representativeness of the reduced 'm' sample from the original sample, which may greatly affect the efficiency scores (Da Cruz and Marques, 2014). The fourth method is a double-bootstrap procedure from Simar and Wilson (2007) that allows statistical inferences and hypothesis testing in DEA models, therefore facilitating the assessment of potential influencer variables on efficiency, whilst further contributing bias-correcting of the efficiency results generated from the original DEA computation (Yang and Zhang, 2018). This fourth second-stage approach is utilised in this research to overcome the limitations of the other methods outlined above, whilst delivering reliable results for benchmarking water companies and evaluating the factors that may influence their efficiency.

When conducting performance analysis, variable choices are vital for fair and validated results. However, the first choice variables are not always available, and in international benchmarking studies, issues around valuation and exchange rates need to be negated; therefore, proxies are often used to represent the first choice variables (de Witte and Marques, 2010a). Though proxies can offer a useful alternative path to conducting benchmarking, it is not known how accurate some of them are in replacing the first-choice variables. This study therefore assesses the accuracy of two common proxies: population served for the service under review

(Molinos-Senante *et al.,* 2015a; Molinos-Senante and Farías, 2018), which in this instance is drinking water, and water mains pipe network length (de Witte and Marques, 2010a; Mbuvi *et al.,* 2012; Ananda, 2014). These proxies replace the first-choice variables *volume of water produced* and *capital expenditure*, respectively.

Like many countries, England and Wales are serviced by a mixture of water only companies (WoCs) and water and sewage companies (WaSCs), which often prove difficult to analyse collectively due to their differing operations, although attempts have been made (Molinos-Senante *et al.,* 2015b). An effective assessment of these companies together could enhance opportunities for sharing of best practices across a more diverse sample, leading to more improvements in economic and energy efficiency. This paper therefore uses a sample of WoCs and WaSCs, but only focusses on the water production side of the companies.

This study had three objectives. Firstly, to evaluate the naïve and bias-corrected energy and economic efficiency scores of all water utilities in England and Wales. Secondly, to appraise the role of an array of explanatory variables on the efficiency scores. Lastly, to assess the extent to which proxies may influence efficiency rankings and their influencing variables. These objectives collectively contribute valuable insights for academia and the water industry by attempting to fill gaps in the literature. Bias-corrected efficiency evaluation has not previously been undertaken across WaSCs and WoCs, and could offer unique insight into how WaSCs and WoCs compare in terms of efficiency. Furthermore, research of rare explanatory factors influencing energy and economic efficiency may contribute new knowledge to existing theories on how specific factors affect efficiency. Finally, the analysis of how proxy variables can influence efficiency and explanatory factor results could provide a new evidence base on the reliability of alternative metrics to analyse efficiency.

4.2. Methodology

To estimate the energy and economic efficiencies of WaSCs and WoCs in England and Wales, in addition to the elements influencing their efficiencies, the DEA double-bootstrap method incorporating a truncated regression was employed. The process allowed bias-corrected efficiencies to be ascertained and enabled evaluation of the indicators that affect these efficiencies. Broader benefits of the approach have been outlined in the previous section.

4.2.1. Original DEA model

DEA was initially created by Farrell (1957), then subsequently advanced by Charnes *et al.* (1978). It is a non-parametric procedure that applies linear programming to construct an efficient production frontier. The frontier establishes the comparative efficiency of the sample of units, by comparing their input and output relationships, relative to others in the sample (Charnes *et al*., 1978). Technical efficiency for the DMUs is then ascertained by appraising their distances from the frontier.

The DEA model can be input or output-orientated. Water utilities lack dominant control of their fundamental service output, that being volume of water delivered in this study. However, they do have more control over inputs; accordingly, this paper applied an input-orientated design. The variation of the DEA model used here was established on varying returns to scale, allowing for scale effects. This assumption was considered credible as the sample of water utilities vary in size and are therefore prone to producing different levels of outputs with similar levels of inputs. This judgement is supported by the majority of literature utilising similar methods within the water sector (Peda *et al.,* 2013; See, 2015).

Given j = 1, 2…, N units, each applying a vector of M inputs $x_j = (x_{1j}, x_{2j}, \dots, x_{Mj})$ to generate a vector of S outputs $y_j = (y_{1j}, y_{2j}, \dots, y_{Sj})$, the input-orientated DEA model is expressed as:

$$
\begin{aligned}
& Min\ \theta_j \\
& s.t. \\
& \textstyle\sum_{j=1}^{N} \lambda_j x_{ij} \leq \theta x_{i0} && 1 \leq i \leq M \\
& \textstyle\sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{r0} && 1 \leq r \leq S \qquad\qquad (4.1) \\
& \lambda_j \geq 0 && 1 \leq j \leq N
\end{aligned}
$$

θ_j is a scalar, which indicates the efficiency of the evaluated unit via the given value, which is deemed efficient when $\theta_j = 1$ and inefficient when $\theta_j > 1$. M is the quantity of inputs, S is the quantity of outputs generated, N is the quantity of water companies analysed and λ_j is a collection of intensity variables that represent the weighting of each unit j within the composition of the frontier.

4.2.2. Double-bootstrap DEA method

The issue that arises with some second-stage DEA methods (discussed further in the Introduction) such as Tobit regression is that they can be inaccurate due to the nature of the standard DEA model. Since the efficiency scores are serially correlated when calculating this model, the efficiency estimates can be biased, and any inferences made about explanatory factors can be incorrect (Hoff, 2007; Simar and Wilson, 2007).

To calculate efficiency utilising DEA, but removing errors and potential biases, whilst enabling an analysis of the effect of explanatory factors, Simar and Wilson (2007) developed a double-bootstrap methodology. The model functions by simulating the distribution of the sample by mimicking the data-generation process (Chernick and LaBudde, 2011); the research in this paper generated 2,000 bootstrap samples. The efficiency results then are re-calculated using the new generated data, the divergence between the original values and the more robust values from the double-bootstrap approach reveals the extent of bias that could have distorted the results when using other methods. The full computational operation is defined beneath:

8. Estimate the DEA input-efficiency scores θ_j for all water utilities in the sample using equation 4.1.
9. Perform a truncated maximum likelihood estimation to regress θ against a group of explanatory variables z_j, $\theta_j = z_j\beta + \varepsilon_j$, and produce an estimate $\hat{\beta}$ of the coefficient vector β and estimate $\widehat{\sigma_\varepsilon}$ of σ_ε, the standard deviation of the residual errors ε_j.
10. For each utility j ($j = 1, \ldots, N$) repeat the succeeding steps (3.1-3.4) B_1 times to acquire a set of B_1 bootstrap estimates $\widehat{(\theta_{jb})}$ for $b = 1, \ldots, B_1$.

    10.1. Generate the residual error ε_j from the normal distribution N (0, $\widehat{\sigma_\varepsilon^2}$).

10.2. Compute $\theta_j^* = z_j\hat{\beta} + \varepsilon_j$.

10.3. Generate a pseudo set (x_j^*, y_j^*) where $x_j^* = x_j$ and $y_j^* = y_j(\frac{\theta_j}{\theta_j^*})$.

10.4. Using the pseudo set (x_j^*, y_j^*) and equation 4.1, estimate pseudo efficiency estimates $\widehat{\theta_j^*}$.

11. Compute the bias-corrected estimator $\widehat{\theta_j}$ for each unit j $(j = 1, \dots, N)$ using the bootstrap estimator or the bias $\widehat{b_j}$ where $\widehat{\theta_j} = \theta_j - \widehat{b_j}$ and $\widehat{b_j} = (\frac{1}{B_1} \sum_{b=1}^{B_1} \widehat{\theta_{jb}^*}) - \theta_j$.

12. Use the truncated maximum likelihood estimation to regress $\widehat{\theta_j}$ on the explanatory variables z_j and provide an estimate $\widehat{\beta^*}$ for β and an estimate $\widehat{\sigma^*}$ for σ_ε.

13. Repeat the succeeding three steps (6.1-6.3) B_2 times to obtain a set of B_2 pairs of bootstrap estimates $(\widehat{\beta_j^{**}})$, $(\widehat{\sigma_j^{**}})$ for $b = 1, \dots, B_2$.

13.1. Generate the residual error ε_j from the normal distribution $N\ (0,\ \widehat{\sigma^{*2}})$

13.2. Calculate $\widehat{\theta_j^{**}} = z_j\widehat{\beta^*} + \varepsilon_j$.

13.3. Use truncated maximum likelihood estimation to regress $\widehat{\theta_j^{**}}$ on the explanatory variables z_j and provide as estimate $\widehat{\beta^{**}}$ for β and an estimate $\widehat{\sigma^{**}}$ for σ_ε.

14. Construct the estimated $(1-\alpha)\%$ confidence interval of the n-th element, β_n of the vector β, that is $[Lower_{an}, Upper_{an}] = [\widehat{\beta_n^*} + \widehat{a_a}, \widehat{\beta_n^*} - \widehat{b_a}]$ with

$$Prob\left(-\widehat{b_a} \le \widehat{\beta_n^{**}} - \widehat{\beta_n^*} \le \widehat{a_a}\right) \approx 1 - a$$

The model was solved using ‘R’, a statistical computing software with the package ‘rDEA’ created by Simm and Besstremyannaya (2016).

4.2.3. Data description

The same sample of companies was used for both the energy and economic analyses, comprising a mix of ten WaSCs and seven WoCs from England and Wales. All data was for the year 2017-18 and was acquired through the ‘PR19’ data tables that must be submitted alongside business reports to the regional regulator, OFWAT (2020). Despite being secondary data, the quality was deemed sufficient due to the audits and controls implemented by the individual companies along with OFWAT. Thus, it is assumed that key data needed to run the model has been validated. The source files separated water production and wastewater operations, therefore enabling a fair comparison of just the water production side of all companies, whereas evaluation of the data via less granular sources may have led to errors. The resolution of the data is based on an entire year of operation, unless stated otherwise due to model requirements or the nature of specific indicators.

When utilising DEA, the sample size is required to satisfy a minimum size threshold in order to bypass relative efficiency discrimination problems. As the size of the sample was small in this study, 'Cooper's rule' was used in an attempt to avoid discrimination problems. 'Cooper's rule' specifies the quantity of units must be ≥ max$\{m\ x\ s; 3(m+s)\}$ where m represents inputs and s represents outputs (Cooper *et al*., 2007). The energy model used one input and one output, whilst the economic model used two inputs and one output; therefore, the minimum threshold was met. Moreover, a bootstrap approach within the DEA framework enables rigorous efficiency results despite a limited sample size (Molinos-Senante *et al*., 2018a). Nonetheless, it should be noted that the constrained sample size could exaggerate results at either end of the efficiency spectrum. If the sample was large enough to enable more variables within one model, instead of requiring two separate models, results could differ. However, this limitation is difficult to overcome, given the limited number of water utilities in the UK.

The array of variables is critical for a DEA model to generate credible outcomes (Zhu, 2014). The energy model consisted of the sole input of *energy consumed*, which was the total amount of energy consumed in the year by water supply operations measured in kWh. The economic model encompassed *operational expenditure (OPEX)* and *capital expenditure (CAPEX)* as inputs; both models had *volume of water produced* as the only output. These variables were chosen because they represent the essential resources required for a water utility to function and the core operations and services that they provide. Furthermore, the indicators are concurrent with the literature (Peda *et al.,* 2013; Mardani *et al.,* 2017; Molinos-Senante and Farías, 2018). Although the variables cover the essential activities of water companies, it should be noted that the approach is not as holistic as alternative methods of performance evaluation such as life cycle analysis or emergy accounting (Arden *et al.,* 2019), which would cover many different aspects of the water supply process in a narrower scope. *OPEX* and *CAPEX* data contained spending on third party services, and included wholesale and retail aspects of the companies. Using *CAPEX* over a single year has the potential misrepresent usual spending, therefore projected year-on-year capital expenditure change over the next four years was averaged for all companies, displaying an anticipated -5.43% average change. This was deemed an acceptable level of variation to validate the use of *CAPEX* over the 2017/18 year. Furthermore, *CAPEX* was used assuming that the utilities contribute enough capital to renew and maintain the distribution network long-term. As many studies have used proxies to replace key inputs and outputs, this paper reviewed how accurate the use of two common proxies are. The proxies were *population served for drinking water* and *length of water mains*, which replaced the output *volume of drinking water produced* and the input of *CAPEX*, respectively.

An elemental contributor of resource use for water companies is the quality of water they supply (Plappally and Lienhard, 2012). Utilities within efficiency analyses should not be penalised for contributing superior quality outputs than others; accordingly, this paper follows Saal *et al.,* (2007) and Walker *et al.*, (2019), and modifies the output variable that is used for both the energy and economic assessments according to water quality. The *volume of water produced* was amended by the quality of that water (y_1) as reported by the companies to the regulators Environment Agency and OFWAT. The indicator for water quality was reported as a percentage, with 100% expressing that all obligations are met; this was then converted to decimals and employed as a multiplier for the original output variable:

$$y_1 = WP \times DWQ \quad (2)$$

The *volume of water produced* is represented by WP and DWQ is drinking water quality. The resulting figure once adjusted then constituted the single output for the energy and economic DEA analyses.

In order to deduce reasons for the efficiency results and performances of companies, five explanatory variables were chosen for evaluation. The variables were *leakage*; *consumption per capita*; *number of abstraction sources*; *average pumping head height* (across raw water abstraction, treatment and transport); and *proportion of water passing through treatment plants sizes 5-8*, which are the largest treatment plants (total scale is measured from 1-8, OFWAT, 2019). These variables were chosen because they are deemed to affect efficiency, and in some cases, have not been studied before – e.g., *proportion of water passing through the largest treatment plants* and *average pumping head height*. Treatment plants are viewed to operate at economies of scale (Molinos-Senante and Sala-Garrido, 2017) but testing the limits to this within the context of other variables has seldom been done*. Pumping head height* is interesting to investigate, as a larger head would naturally cost more money to operate (Berg, 2013), however, the significance on cost and energy relative to the efficiency of a company is unknown. All the variables used in this research including inputs, outputs, proxies, explanatory variables and quality variables are summarised in Table 4.1.

Table 4.1. *Summary of the 2017/18 data used in the DEA analyses displayed to three significant figures where possible. Data from the PR19 company reports available via OFWAT (2020).*

		Average	SD	Minimum	Maximum
Inputs	Energy (kWh)	212,706	151,759	24,084	558,178
	Operational expenditure (million£)	211	173	22	639
	Capital expenditure (million£)	148	127	8	512
Output	Volume of water produced (Ml/day)	726	569	52	2,169
Proxies	Length of water mains (km)	12,016	13,711	2,627	46,540
	Population with water service	3,460,133	2,714,840	218,918	10,012,827
Explanatory variables	Leakage (Ml/day)	190	179	14	695
	Consumption per capita (l/h/day)	144	8	129	159
	Number of abstraction sources	102	67	9	235
	Proportion of water passing through treatment works sizes 5-8 (%)	74	18	32	98
	Average pumping head height (m.hd)	34	8	17	46
Quality variable	Water quality compliance (%)	99.96	<0.001	99.93	99.98

4.3. Results and Discussion

4.3.1. Energy efficiency results

The results from the input-orientated distance function utilised in this study means scores of 1 are the most efficient, and those companies are operating at the frontier. Conversely, the more scores increase above 1, the further those companies are away from the frontier and thus the less efficient they are. The standard DEA model (equation 4.1) results represented as 'non-bias corrected scores' in Figure 4.1 estimated three of the 17 companies to be operating at the efficiency frontier with estimates of 1. The implication of this is that those companies cannot reduce their energy consumption any further, whilst also maintaining their drinking water delivery levels. The mean efficiency of the whole sample was 8.258 with a standard deviation of 6.462. Efficiency scores are based on all other aspects being equal, which is where exploring exogenous variables becomes important. A comprehensive display of the precise efficiency estimates, the rankings, and the confidence intervals for all the following sections are available in Supplementary Information.

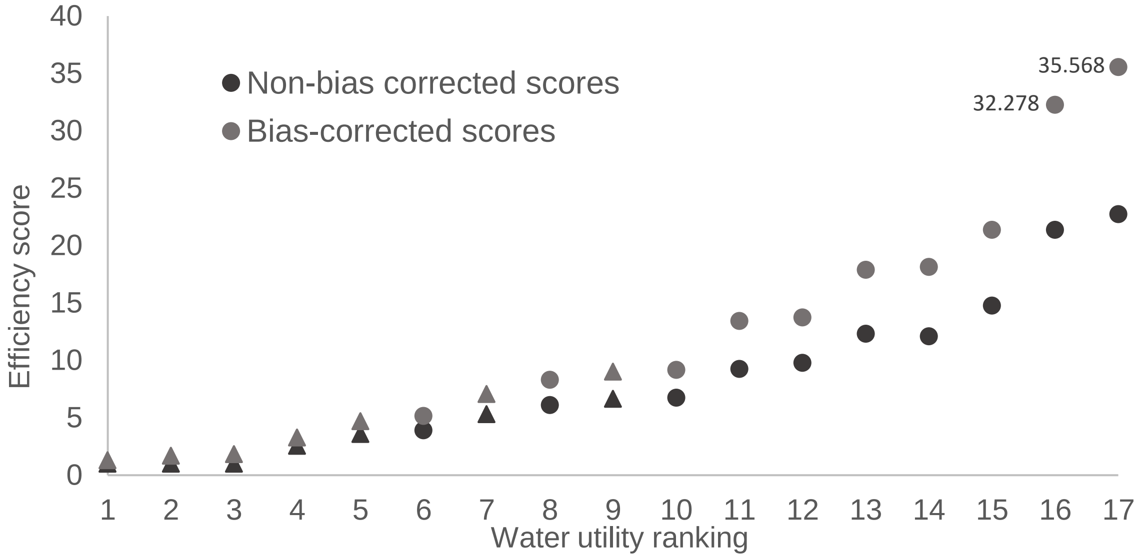

Figure 4.1. *Rankings established from the original DEA model and bias-corrected DEA results produced with 2000 bootstrap iterations for the energy performance across 17 water companies in England and Wales. WoCs are featured as triangles and WaSCs are displayed as circles.*

Utilising the double-bootstrap method estimates that the whole sample was less efficient than the standard DEA model indicated (Figure. 4.1), which is an expected occurrence with this method. The average bias taken out of the sample with the double-bootstrap method was -3.746, with a minimum value of -0.286 and maximum value of -12.8. Interestingly, although the bias taken out of the sample was large, it only changed the rank of two companies, swapping ranks 13 and 14 around. This result is rare and contrasts with other research (e.g., Ananda, 2014; Gómez *et al.*, 2017; Molinos-Senante *et al.*, 2018a; Molinos-Senante and Sala-Garrido, 2019; Walker *et al.*, 2019) where their biases resulted in many rank changes. An explanation for this result could be that the sample is not large and does not lend itself to many rank changes naturally. Perhaps more importantly, the fact that there were broad efficiency distances between many companies within the sample meant that even large biases taken out did not affect ranking.

Since bootstrapping generates data from the original sample, there are slight variances in the estimates that are generated; therefore, three repeat tests were conducted to ensure that any variances were not large enough to make the study invalid and the following sections will comment on the variance of the results. Three repeats was chosen as this was enough to provide validity to results and could capture any significant variances. For energy bias-corrected results, the average difference in the results was 0.56%, with a range of -1.11%-1.56%. The bias-corrected efficiency scores had a mean average of 12.005, with a standard deviation of 9.996. This implies that the average water company in England and Wales could decrease inputs by 91.7% and maintain the same output standards of water delivery, if they were to perform at the same level as the best performers. The non-bias corrected scores indicated an average potential theoretical reduction of 87.8% (1-1/8.26), marginally lower in contrast to the bias-corrected average. The large average potential reduction is symptomatic of having a large spread in efficiency estimates using the DEA method, where some companies were perceived to be significantly less efficient than others, highlighted by the range of the sample being 1.286-35.568.

The reason for the large range of efficiency estimates appears to have been due to the sample including WaSCs and WoCs. Figure 4.2 shows that the top five performing companies are WoCs and only three WaSCs are amongst the WoCs altogether. Within the top ten performers, the efficiency estimates are relatively close (1.286-9.202) compared to the following seven companies (13.465-35.568), showing that there are clear efficiency disparities between companies that only deliver drinking water compared to the companies that deliver water and treat wastewater. This was a surprising result, since the study only focussed on the drinking water aspects of the businesses. One explanation could be that some companies are hindered by exogenous variables. A further potential explanation is that the WoCs only have the drinking water elements to focus on and thus have optimised their operations in this field, whereas the WaSCs also have the wastewater treatment components to provide, therefore optimisations such as replacement of inefficient pumps or leakage reduction measures are not prioritised. A further explanation could be that for WaSCs, there was inadequate separation of water treatment and water supply data. Following the results, further checks were conducted to ensure information was extracted correctly from the data sources; however, the sources could have incorrect data separation.

When conducting the energy efficiency analysis, *population served for water consumption* showed to be an appropriate proxy for *volume of water produced*. Figure 4.2 shows that the ranks of all the companies remained the same when the proxy was in use. The only impact the proxy variable had on energy efficiency analysis of the companies was that 14 of them displayed a reduction in their efficiency score, exhibiting an average of 0.172 reduction, equivalent to 1.01% compared to the results from the original variable of *volume of water produced*.

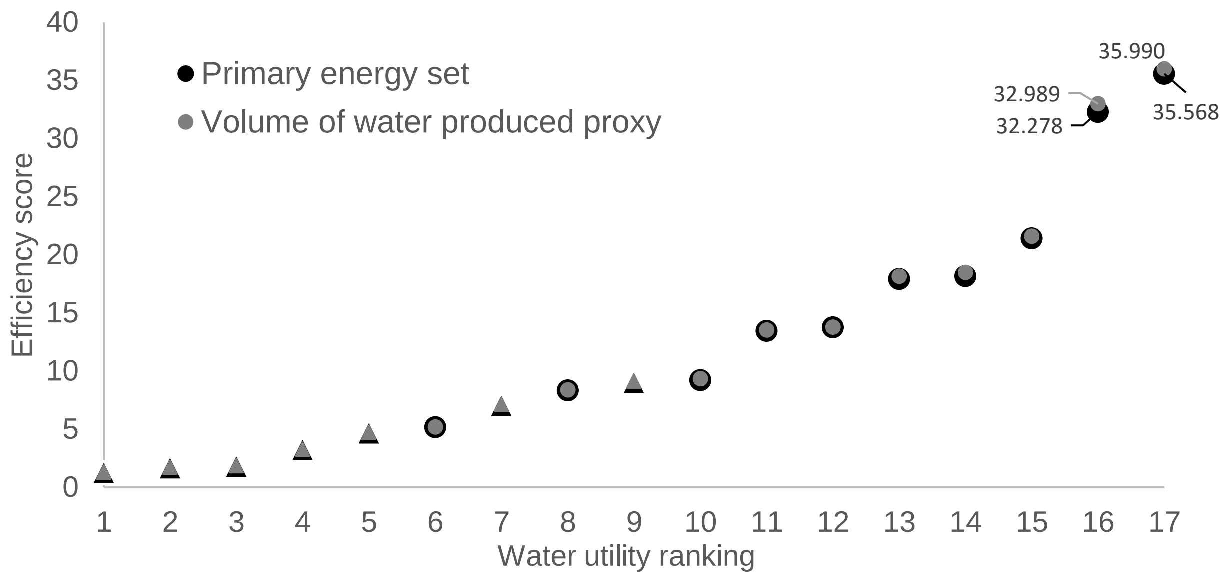

Figure 4.2. *The bias-corrected (2000 bootstrap iterations) energy efficiency scores and ranking with the primary set of variables, and a volume of water produced proxy (population served for drinking water). WoCs are featured as triangles and WaSCs are displayed as circles.*

4.3.2. Role of explanatory factors on energy efficiency

An essential element of the double-bootstrap approach is the ability to appraise explanatory factors that may affect efficiency by employing a bootstrap truncated regression model. The explanatory factors analysed in this research were *leakage*, *per capita consumption*, *number of sources*, *proportion of water through size 5-8 water treatment plants* and *average pumping head height*; their influence on efficiency is presented in Table 4.2. A negative impact on efficiency is recognised if the bias-corrected coefficient value is positive and vice versa, and an asterisk is marked next to the coefficients to highlight significance to the 5% level. The variance average in the repeat tests for the bias-corrected coefficients was 1.03%, with a range of -2.03%-1.91%.

Table 4.2. *Results of bootstrap truncated regression (bias-corrected) with 2000 iterations for energy efficiency assessment using the first-choice variables and volume of water produced proxy: population served for water production.*

	Primary energy set			Energy WP replaced		
Explanatory factor	**Coefficient**	**Low**	**High**	**Coefficient**	**Low**	**High**
Leakage (Ml/day)	0.045*	0.031	0.059	0.046*	0.032	0.060
Number of sources	0.053*	0.008	0.097	0.053*	0.011	0.097
Average pumping head height (m.hd)	0.423*	0.136	0.736	0.426*	0.136	0.729
Proportion of water through size 5-8 treatment plants (%)	0.142	-0.033	0.323	0.140	-0.029	0.318
Per capita consumption (l/h/d)	-0.134	-0.391	0.116	-0.144	-0.410	0.111

Note: *Statistically significant at the 5% level.

Leakage had a significant negative effect on energy efficiency, as to be expected since the more water that is lost, the more water needs abstracting, treating and delivering, which all require energy. Energy efficiency studies on water utilities that evaluate explanatory factors are rare. Walker *et al*. (2019) evaluated the environmental efficiency of water utilities in terms of carbon intensity, and found no significant link with *leakage*, although they did incorporate embodied carbon as well as operational carbon over just a one-year period, therefore one single significant capital project may have skewed the data depending on method of amortisation.

The variable *consumption per capita* had a positive relationship with energy efficiency to a non-significant extent. Although greater consumption overall would increase energy consumption due the requirements to pump and treat a larger volume, there are links to economies of customer density too, which can distort results (Byrnes *et al.*, 2010). When a pipe network is established, the volume of water actually flowing through it has nominal energy consumption and economic costs. In this instance, the insignificant relationship means inferences on reasoning are just speculative.

Results in Table 4.2 indicate that, as the *number of sources* increases, energy efficiency reduces. Although diversifying abstraction sources can be a positive attribute for companies to make their supply more resilient, it appears as though this is at the expense of a significantly increased energy consumption owing to more pumping being required through a larger network of piping. For benchmarking and regulation, this is a relationship to be aware of; however, water managers do not have much control over this factor, which is often determined by the magnitude of locally available supplies; therefore, any penalties on companies performing poorly on this metric need to carefully consider this context.

The *proportion of water passing through the largest four sizes of treatment works* was surprisingly associated with inefficiency, albeit insignificantly. The anticipated result was that economies of scale at the treatment level (Molinos-Senante and Sala-Garrido, 2017) would mean the more water being treated at larger treatment works, the more efficient energy use would be. An explanation of this could be that any economies of scale that are experienced are offset by the increase in the distribution of water to centralised treatment plants as Kim and Clark (1988) found, along with the increased leakages that occur over larger pipe network (<0.001 p-value using Pearson’s r for relationship between *leakage* rates and network length found). Furthermore, scale economies are seen to be lost in treatment plants once they attain a certain size (Hernández-Chover *et al.,* 2018), therefore this would weaken any relationship in the data.

Average pumping head height showed a significant influence on energy inefficiency, meaning as the pumping head increases, so efficiency declines. This was anticipated, as pumping is a major consumer of energy for water utilities and the head is a pivotal facet of this consumption (Filion *et al.,* 2004; Díaz *et al.,* 2011). Water practitioners have no influence over pumping heads once infrastructure is in place, but this result does display how important it is for engineers and designers to minimise the head height when developing any part of the network to ensure long-term energy sustainability.

The *population supplied with water* also served as a useful proxy for the *volume of drinking water* produced in terms of evaluating the explanatory factors. The right half of Table 4.2 shows that the direction of the efficiency effect remained the same, as did the variables that showed significance.

4.3.3. Economic efficiency results

The non-bias corrected scores for economic efficiency results (Figure 4.3) indicated that three of the 17 utilities are on the efficiency frontier, with a score of 1. The mean efficiency of these non-bias corrected estimates across the 17 companies was 9.321 with a standard deviation of 8.294, suggesting that an average UK water company can reduce their *OPEX* and *CAPEX* inputs by 89% and still produce their water production output to the same level.

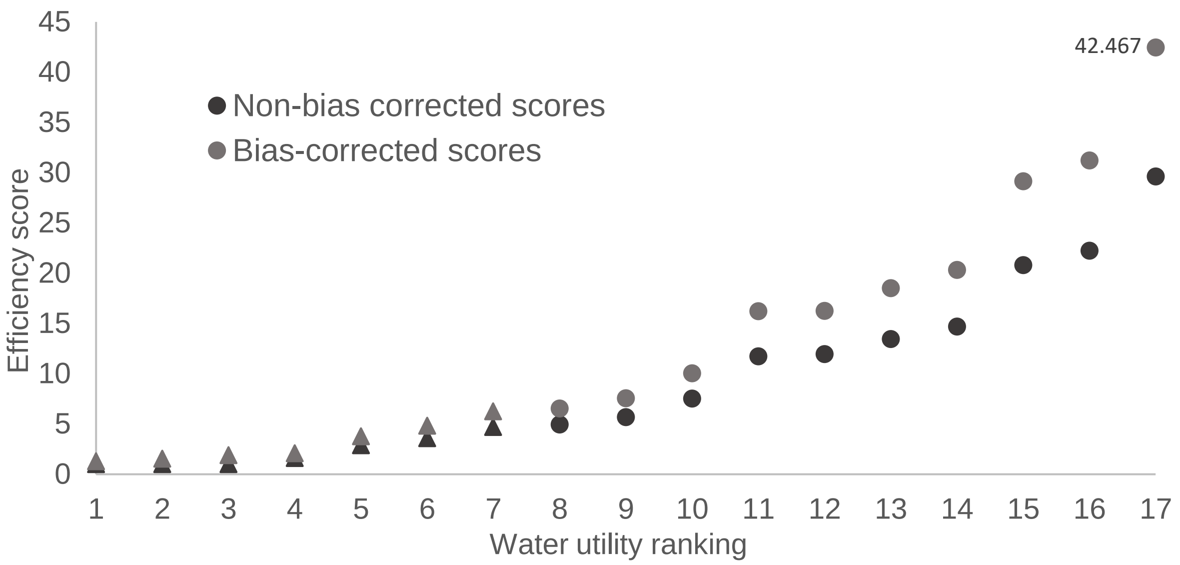

Figure 4.3. *Rankings established from the original DEA model and bias-corrected DEA estimates produced with 2000 bootstrap iterations for the economic performance of 17 England and Wales water companies. WoCs are featured as triangles and WaSCs are displayed as circles.*

The bias taken out of the economic results ranged from -0.286 to -12.821, and averaged at -3.618. Despite the considerable bias taken out of the sample, it did not affect the rankings of the companies. This result contradicts other research (Ananda, 2014; See, 2015; Gómez *et al.*, 2017; Molinos-Senante and Sala-Garrido, 2019) where their biases altered the rankings of most of the sample. A potential justification for this is similar to that in the energy results in that the sizable efficiency spans between utilities proceeded to absorb biases taken off efficiency scores.

The bias-corrected efficiency results had a mean average of 12.94, with a standard deviation of 11.773. The variance in the three repeat tests was averaged at 0.78% with a range of -

1.47%-2.01%. The average corrected efficiency scores indicated that an average water utility could scale down their collective *OPEX* and *CAPEX* by 92.3%, whilst producing the same amount of drinking water. This is particularly large compared to the Walker *et al*. (2019) study on UK and Irish water and sewerage utilities, where they calculated that the average utility could decrease their economic inputs by 19.4%. A possible reason for this was alluded to in Section 4.3.1, that having such a large theoretical drop in inputs is likely a result of the very considerable range in efficiency scores (1.286-42.467) brought about seemingly by the mixture of WaSC and WoCs in the sample. Figure 4.3 shows that all WoCs were ranked higher than the WaSC for economic efficiency, despite the data encompassing just the water production side of operations for all companies. An explanation explained earlier in Section 4.3.1 is that WaSCs may find it more difficult to disseminate and effectively utilise resources due to the extra operational strain of wastewater treatment compared to WoCs. Moreover, an array of exogenous can influence the efficiency results and cause the disparity between companies (main exogenous factor evaluation in Sections 4.3.2 and 4.3.4). For example, a justification appears to be linked to size; the bias-corrected coefficients were naively tested for correlation using Pearson's r against *population with water service* as an indicator to represent the size of the water utilities, and a positive correlation with a p-value value of <0.001 was found. This suggests that the larger companies are, the less efficient they are at producing water at lower costs. Since generally WoCs are smaller than WaSCs, with seven of the smallest eleven companies in this sample being WoCs (see Supplementary Information for breakdown), it appears size could at least partially explain the reason behind WoCs outperforming WaSCs. It is not clear why size has this correlation; *population density* was also correlated against coefficient values to test a reason behind the size result and this showed to have no impact (p-value of 0.153). It is possible that larger-scale operations are harder to manage efficiently, with the larger network, more abstraction and more sources of abstraction making companies more inefficient. The disparity of efficiency between WaSCs and WoCs is an area where future research could investigate; perhaps analysing factors such as precipitation, types of abstraction sources, topography and governance structures.

The proxies analysed for the economic analysis were *km of water mains* replacing *CAPEX* and *population served for drinking water*, which replaced *volume of water produced*. The latter appeared to be a satisfactory proxy, with only two companies (this ranks 11 and 12) exchanging places (Figure 4.4). If the sample were larger and closer in terms of efficiency range, then perhaps there would have been more ranking changes. The *CAPEX* proxy resulted in ten companies changing their rank compared to the original primary set of indicators, with 11 ranks moved (Figure 4.5). A further effect of the *CAPEX* proxy was the increased efficiency of the sample, implying companies were on average 12.63% more efficient. Some companies exhibited particularly large increases in efficiency, for example, ranks 16 and 17 went from 31.222 and 42.467 to 24.661 and 17.059 respectively. As more than half of the sample changed rank and some utilities experiencing such large changes, using the *length of mains* network does not appear be an apt proxy for *CAPEX*.

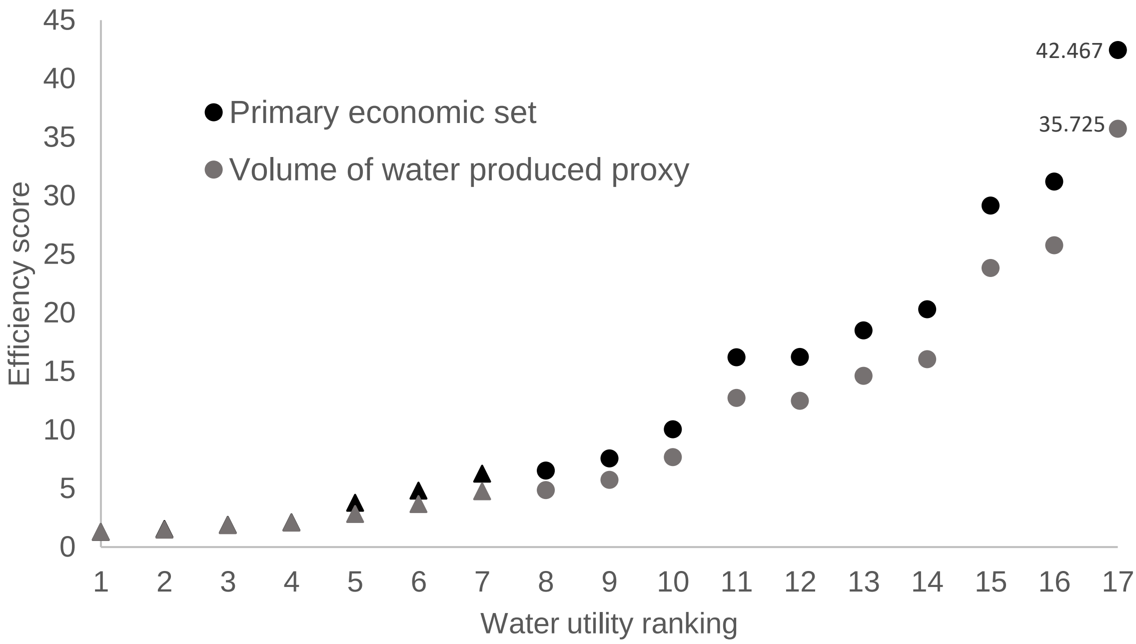

Figure 4.4. *The double-bootstrap (2000 iterations) bias-corrected economic efficiency results with the primary set of economic variables, and a volume of water produced proxy (population served for drinking water). WoCs are featured as triangles and WaSCs are displayed as circles.*

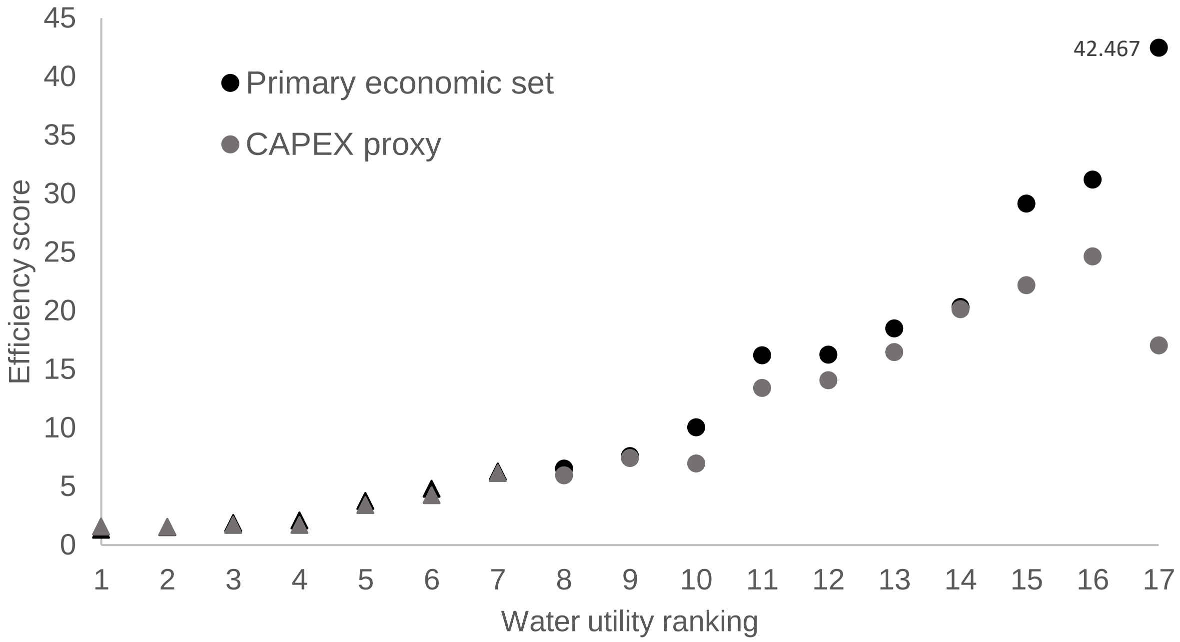

Figure 4.5. *The double-bootstrap (2000 iterations) bias-corrected economic efficiency results with the primary set of economic variables, and a capital expenditure (CAPEX) proxy (kilometres of water mains network). WoCs are featured as triangles and WaSCs are displayed as circles.*

4.3.4. Role of explanatory factors on economic efficiency

The explanatory factors analysed in the economic assessment matched those analysed for energy efficiency; *leakage*, *per capita consumption*, *number of sources, proportion of water through size 5-8 water treatment plants* and *average pumping head height*. As mentioned in Section 4.3.2, the bias-corrected coefficients for the explanatory variables (Table 4.3) are regarded to adversely affect efficiency when their figures are of a positive value and positively influence efficiency if their figures are negative. The average variance in the three repeat tests was 1.08% (range of -2.47%-0.79%).

Table 4.3. *Results of bootstrap truncated regression (bias-corrected) with 2000 iterations for economic efficiency analysis using the first-choice variables, volume of water produced proxy: population served for water production, and CAPEX proxy: kilometres of water mains network.*

	Primary economic set			Economic CAPEX replaced			Economic WP replaced		
Explanatory factor	**Coefficient**	**Low**	**High**	**Coefficient**	**Low**	**High**	**Coefficient**	**Low**	**High**
Leakage (Ml/day)	0.054*	0.041	0.067	0.016	-0.003	0.036	0.046*	0.037	0.056
Number of sources	0.053*	0.017	0.093	0.079*	0.025	0.140	0.041*	0.013	0.072
Proportion of water via size 5-8 treatment plants (%)	0.158*	0.005	0.325	0.238*	0.016	0.532	0.125*	0.010	0.251
Average pumping head height (m.hd)	0.205	-0.058	0.470	-0.013	-0.396	0.396	0.177	-0.023	0.389
Per capita consumption (l/h/d)	-0.121	-0.343	0.103	-0.358*	-0.763	-0.001	-0.076	-0.249	0.095

Note: *Statistically significant at the 5% level.

The variable *leakage* mirrored the energy analysis and had a significant negative influence on economic efficiency. This result is concurrent with the majority of similar studies (Berg, 2013; See, 2015); however, this is not always the case. Some research shows the negative affect on efficiency to a non-significant extent (Marques *et al.,* 2014). Moreover, there are articles that demonstrate the opposite relationship, with *leakage* appearing to cause efficiency (de Witte and Marques, 2010a; Ananda, 2014) albeit, to a non-significant degree. The leakage result in our research is a particularly interesting result for the UK since water companies operate under the ‘sustainable economic level of leakage’, where they are required by the regulator OFWAT (2019) to fix leaks, as long as the cost of doing so is less than the cost of not fixing the leak. The suggestion is therefore that leakage is less likely to be at such a rate that it significantly negatively affects economic efficiency however, due to other factors obscuring the time when replacement of pipes should occur, this may not be the case.

Consumption per capita displayed a positive relationship to a non-significant level, therefore also matching the energy explanatory factor results. As examined in Section 4.3.2, the contradiction in the expected result is likely to be from the links to economies of customer density that can relieve increased *consumption per capita* from having such a strong influence (Byrnes *et al.,* 2010; Carvalho *et al.,* 2012). The volume customers consume is not directly controllable by water managers, however, there have been awareness campaigns and water efficiency information and technology available to customers from companies to reduce user consumption that have had some affect. Manouseli *et al.* (2019) evaluated the effectiveness of the water efficiency initiatives rolled out by water companies in England, and found that households that participated in the programme reduced their consumption by approximately 15%. Perversely, water conservation is bad for companies in terms of short-term profits, although it does provide benefits to wider society. The companies will however benefit in longer-term sustainability as water is expected to become scarcer in the UK due to climate change (Arnell and Delaney, 2006; Wade *et al*., 2013) and reduced consumption can reduce the frequency for requiring new infrastructure.

The *number of abstraction sources* was significantly associated with negative economic efficiency, again following the energy results. This was anticipated, as more materials are required such as pumps, piping and associated infrastructure to utilise more sources, thus increasing costs. This result shows that when increasing resilience of the water supply by increasing the number of sources, there is a trade-off, where efficiency lowers. Many companies may not have a choice of how many abstraction sources they utilise, furthermore the perfect balance of resilience and efficiency a company's number of sources is not yet known. Therefore, as noted in Section 4.3.2, any regulators conducting fines or punishments on companies for poor efficiency should consider such results.

The most unexpected result for variables that influence economic efficiency was the *proportion of water treated by size 5-8* (the largest) treatment plants. Table 4.3 indicates a significant negative influence on economic efficiency, deviating from the energy explanatory factor analysis. The economies of scale present at larger treatment plants was expected to result in a positive relationship with efficiency. Reasons for this are similar to those outlined for the role this variable had in energy efficiency (Section 4.3.2); greater pumping, maintenance and leakage costs from extended pipe networks and loss of scale economies at particular sizes (Hernández-Chover *et al.,* 2018), despite treatment plants being positively associated to economies of scale (Molinos-Senante and Sala-Garrido, 2017). For companies to take advantage of economies of scale in treatment plants to improve their economic and energy efficiency then, there is a need for better understanding of the multiple factors influencing efficiency across different sizes of plant, considering associated consequences for distribution effects.

The *pumping head average* was regarded to have a non-significant negative effect on economic efficiency, diverging from the energy results, which showed the same effect on efficiency, but with significance. Despite the higher energy demands that larger pumping heads create, the non-significant result indicates that energy costs are not the dominant factor in economic efficiency, which is supported by power (including climate change levy and carbon reduction commitments) representing an average of 10.8% of total *OPEX* for this sample.

Table 4.3 presents how the simple proxy of *population supplied with water* adequately replaced *the volume of water produced*, since the significance and direction of influence of explanatory factors on efficiency were the same. The satisfactory performance of the *volume of drinking water* proxy was expected to an extent, since the water produced is for the proxy of *population served for drinking water*. The proxy would theoretically match the original variable perfectly were it not for erroneous factors such as *leakage* and *per capita consumption*, which for this sample ranged from 15.8%-32% and 129-159 (l/h/d), respectively, which appeared to be not enough to skew the appropriateness of the proxy. The *CAPEX* proxy of *water mains network length,* however, was less successful. It only directly matched two of the variables: *number of sources* and *proportion of water through size 5-8 water treatment plants*, for both direction of influence and significance. The proxy did match the direction of influence of the true *CAPEX* variable for *leakage* and *per capita consumption* however, significance of relationship was lost. Finally, for *average pumping head height*, the proxy misinterpreted the direction of efficiency affect, the result suggesting that larger pumping heads actually resulted in higher economic efficiencies.

4.4. Conclusions

The goals of this research were to implement a double-bootstrap DEA method to compare unbiased energy and economic efficiency between a mixture of water only companies and water and sewerage companies, to evaluate the effect of explanatory factors, and to analyse the accuracy of two common proxies. Results support four main conclusions. Firstly, that the average company could decrease their energy inputs by 91.7% and their economic inputs by 92.3%, if they were to perform at the efficiency frontier (in the absence of significant exogenous influences). Thus, we establish that there is substantial scope to improve energy and economic efficiency for water utilities in England and Wales, if the practices of best performers were widely adopted. There was a large variance in the potential reductions of inputs, which appeared to reflect the second main conclusion – that WoCs generally performed much more efficiently than WaSCs. All seven WoCs outperformed WaSCs in the economic analysis they were amongst the top nine performers in the energy analysis. Improper separation and reporting of operational data from companies into their reports may have been a reason for this, however exogenous factors likely played the major role. Size appeared to be a key determinant, displaying a positive relationship with efficiency and p-value of <0.001 when correlated with efficiency scores, but further research is recommended to investigate the complex influence of size. Thirdly, the paper determined factors that influence efficiency. Of the potential explanatory variables analysed, *leakage* and *number of abstraction sources* were concurrent in their negative effect and significance across both the energy and economic assessments. *Average pumping head height* displayed a significant negative affect for energy, whereas the variable *proportion of water passing through the largest four treatment works* was deemed to have a significant negative effect on economic efficiency. These exogenous factors therefore need to be corrected for in future benchmarking activities and have the potential to inform water companies about factors to prioritise in order to improve efficiency. The final conclusion was that the proxy *population served for drinking water* can adequately replace *the volume of water produced* as an input variable in efficiency benchmarking when *leakage* and *per capita consumption* are fairly uniform across the sample, since companies stayed at the same rank and explanatory factors displayed the same significance. Conversely, *length of water mains* performed poorly when replacing *CAPEX* as an economic input, implying companies were on average 12.6% more efficient, resulting in 10 companies changing their rank compared to the original variable and causing some explanatory variables to differ in direction of influence and significance. Further research is recommended on the energy and economic efficiency of WoCs and WaSCs, considering a wide range of exogenous variables and careful selection of (proxy) indicators.

5. Aligning efficiency benchmarking with sustainable outcomes in the United Kingdom water sector

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Abstract

The provision of fundamental services by water and sewage companies (WaSCs) requires substantial energy and material inputs. A sustainability assessment of these companies requires a holistic evaluation of both performance and efficiency. The Hicks-Moorsteen productivity index was applied to 12 WaSCs in the United Kingdom (UK) over a 6-year period to benchmark their sustainability, based on eight approaches using different input and output variables for efficiency assessment. The choice of variables had a major influence on the ranking and perceived operational efficiency among WaSCs. Capital expenditure (utilised as part of *total expenditure*) for example, is an important input for tracking company operations however, potential associated efficiency benefits can lag investment, leading to apparent poor short-term performance following capital expenditure. Furthermore, *water supplied and wastewater treated* was deemed an unconstructive output from a sustainability perspective since it contradicts efforts to improve sustainability through reduced *leakage* and *consumption per capita*. *Customer satisfaction* and water quality measures are potential suitable

alternatives. Despite these limitations, *total expenditure and water supplied and wastewater treated* were used alongside *customer satisfaction* and *self-generated renewable energy* for a holistic sustainability assessment within a small sample. They indicated the UK water sector has improved in productivity by 1.8% on average for 2014-18 and still had room for improvement, as a technical decline was evident for both the best and worst performers. Collectively the sample's production frontier was unchanged but on average companies moved 2.1% closer to it, and further decomposition of productivity revealed this was due to improvements in economies of scale and scope. Careful selection of appropriate input and output variables for efficiency benchmarking across water companies is critical to align with sustainability objectives and to target future investment and regulation within the water sector.

Keywords: Performance Evaluation; Water Companies; Total Factor Productivity; Data Envelopment Analysis; Sustainability assessment; Hicks-Moorsteen productivity index

5.1. Introduction

A reliable and efficient supply of safe, treated water is fundamental to a prosperous society (Martínez-Santos, 2017) however, not all water networks are sustainable under current climate change projections (Zischg *et al*., 2017). When one measures the efficiency and sustainability of water systems they should consider a broad range of variables, including economic, social (e.g., sanitation) and environmental (e.g., carbon emission) impacts. Performance evaluation and benchmarking of water companies is vital to promote efficiency and protect the interest of customers (Zope *et al*., 2019). The number of studies on water company performance analysis has increased in recent years (Lombardi *et al*., 2019), and while this has covered many different locations and times, and applied numerous different methodologies, a more integrated assessment that includes environmental sustainability of water utilities is relatively rare compared to more focussed studies (de Witte and Marques, 2012; Cetrulo *et al*., 2019; Goh and See, 2021).

The majority of benchmarking and performance analysis of the water sector focuses on economic efficiency, as outlined by Abbot and Cohen (2009), Worthington (2014) and Lombardi *et al*. (2019). Amongst the financial indicators in these studies, labour and infrastructure often feature. Research with a focus on other factors are limited, except for a few notable works. Energy consumption is one of the most popular non-financial indicators utilised (although often used as a cost), as can be seen in the de Witte and Marques (2010a) and Krampe (2013) studies, which encompass water supply companies and treatment plants, respectively. More alternative assessments of efficiency include Tsargarakis (2018), who evaluated water company complaints against operational expenditure; Ananda and Pawsey (2019), where they analysed customer service and network reliability; and Haziq *et al*. (2019) that determined the satisfaction levels of customers against services provided. Although such studies have use on their own, a combination of the diversified subject matter outlined above for water companies within one sustainability assessment would offer unique insight, since only a handful of studies have taken this approach previously (e.g., Gill and Nema, 2016;

Molinos-Senante *et al*., 2016a; Murungi and Blokland, 2016; Villarreal and Lartigue, 2017, Pérez *et al*., 2019). Even within these studies, some split up their analyses into separate models, and still do not include energy within any of their approaches (Gill and Nema, 2016; Murungi and Blokland, 2016; Villarreal and Lartigue, 2017) however, prioritising service reliability, water quality, and customer satisfaction in their samples of developing countries is valuable. A holistic view would be particularly poignant considering the significant impact that water companies have on society. For example, the United Kingdom (UK) water industry employs 58,500 people, has an annual turnover of £11 billion (Energy and Utility Skills, 2020), and consumes 3% of national electricity (Majid *et al*., 2020). Furthermore, the array of approaches to analysing efficiency creates questions around the pitfalls and positives of the diverging variables. Selecting the appropriate variables is vital for a valid study as Villegas *et al.* (2019) and Molinos-Senante and Maziotis (2020a) displayed in their studies of England and Wales. Therefore, understanding how the choice of variables relate to the study objective is imperative in order to draw meaningful conclusions.

Measuring efficiency can be an important aspect of complying with sustainability targets, which are often based on the aggregate impact of all consumption, such as fossil energy, resource use, and greenhouse gas emissions (Bonilla *et al*., 2018). Input-orientated efficiency is determined by assessing the levels of outputs relative to the levels of inputs, with the goal being to produce the most outputs with the fewest inputs. Naturally, efficiency results are affected by the choice of inputs and outputs used in the assessment. To investigate how to better evaluate the efficiency of water companies in a sustainability sense, an evaluation of the effects of using different variables that cover social, environmental and economic factors was undertaken. To conduct this, Total Factor Productivity (TFP) was used. In the context of this study, when benchmarking the efficiency of water and sewerage companies (WaSCs), productivity and efficiency are slightly different concepts. Productivity comprises of evaluating performance change over time, thus integrating a temporal element to sustainability analysis (Le *et al*., 2019). Goh and See (2021) reviewed 142 journal articles regarding water utility benchmarking between 2000-2019 and noted TFP was only used as a keyword in seven studies, whilst productivity growth appeared 12 times.

There is an array of indices that have been developed to compute TFP and have been utilised to evaluate water companies. They can be grouped into parametric and non-parametric methods, the former assuming a predefined technology function. The non-parametric approach can further be classified into frontier and non-frontier methods. One of the most common non-frontier methodologies is the Törnqvist productivity index (Berhera and Sharma, 2020; Oulmane *et al*., 2020), which measures the ratio of all the outputs, weighted by the corresponding revenues, to all the inputs, that are weighted by cost, in quantities by using the firms within the sample to be evaluated themselves (Simoes and Marques 2012). Many non-parametric frontier methods are used to compute TFP and have been applied to the water industry, such as the Färe-Primont productivity index (Molinos-Senante *et al.,* 2017a), Malmquist Productivity Index (MPI) (Molinos-Sennante *et al*., 2017b), Luenberger Productivity Index (LPI) (Sala-Garrido *et al.,* 2018), Malmquist-Luenberger productivity indicator (Ananda, 2018; Sala-Garrido *et al*., 2019), and the Hicks-Moorsteen Productivity Index (HMPI) (Molinos-Senante *et al*., 2016b). The essential advantage of these non-parametric frontier methods over parametric methods is that they do not require a priori assumptions about the functional relationship between the variables, which can cause specification and estimation problems (Murillo-Zamorano and Vega-Cervera, 2001).

The MPI, which was introduced by Caves *et al*. (1982), is the most commonly applied method to analyse changes in TFP. The reason for its popularity is that it can be computed without price data and can be broken down into measures of technical and efficiency changes (Shao and Lin, 2016). Despite the numerous positives of MPI, it does have some decisive limitations. O'Donnell (2014) comments that some of the distance functions within the index may be undefined and infeasibility problems might then ensue (Kerstens and Van De Woestyne, 2014). As an outcome, the results from MPI may not accurately express TFP change from scale effects. Moreover, MPI requires a choice of input or output orientation (Molinos-Senante *et al*., 2020), and is deemed inappropriate when the sample operates under variable returns to scale (VRS), as Grifell-Tatje and Lovell (1995) and O'Donnell (2008) demonstrated. VRS refers to a change in inputs that is not directly proportional to a change in outputs (Färe and Primont, 1995). MPI is thus not applicable to many situations.

The limitations that MPI encompasses are largely overcome by the HMPI. Defined as a ratio of the Malmquist input and output indices, while using the Shephard input and output distance functions, respectively (Bjurek, 1998), the HMPI does not require price data and satisfies all other index conditions, including multiplicative completeness and transitivity tests (O'Donnell, 2012). The HMPI thus functions within a simultaneous input and output orientation, and can be computed under both constant returns to scale (CRS) and VRS technologies, giving it a distinct advantage over similar TFP methods like MPI. Furthermore, HMPI makes no assumptions on behavioural aims such as maximising profit, or market settings like regulation and competition (Dhillon and Vachharajani, 2018). Briec and Kersten (2011) highlighted further advantages of HMPI, commenting that under strong input and output disposability, the determinateness axiom is satisfied so that infeasibility problems are avoided. Meaning that the index is well defined even when one or more of its arguments becomes zero or infinity. A feature of HMPI that makes it preferable to other TFP approaches is one it shares with MPI, which is that it can be decomposed into TFP change elements. These components are i) technical change, which measures movements in the production frontier, and ii) efficiency change, that measures unit movement relative to the frontier. Efficiency change can be further broken down into technical efficiency, mix efficiency, residual mix efficiency, scale efficiency, and residual scale efficiency, which collectively analyse movements around the frontier to capture economies of scale and scope (Laurenceson and O'Donnell, 2014). Such decomposition can be useful from the perspective of policy and regulation, with the effect of controls on WaSCs being identifiable through TFP decomposition analysis, enabling better decision-making (Wen *et al.,* 2018).

Although the HMPI has many positive attributes, it has thus far had limited use in applied research, particularly within the water sector, with just Molinos-Senante *et al*. (2016b) using it to study wastewater treatment plants. Meanwhile, TFP has been assessed in the water sector with other methods. For example, Guerrini *et al*. (2018), Molinos-Senante *et al*. (2014b), Molinos-Senante *et al*. (2019), Sala-Garrido *et al*. (2018) all utilise the Luenberger or Luenberger-Hicks-Moorsteen to analyse areas of the water sector from water companies directly to treatment plants. Even within other sectors such as banks, agriculture, manufacturing, energy and ports, the use of HMPI has not been common, as Medal-Bartual *et al*. (2016) and Mohammadian and Rezaee (2020) document.

The aims of this paper were three-fold. Firstly, to analyse the applicability of assorted HMPI variable configurations, then to assess how differing approaches affect results and identify the best variable approach for a comprehensive sustainability evaluation. Secondly, to investigate the productivity change on a sample of UK WaSCs over a six-year period using the variable configuration for sustainability analysis found in the first aim. Finally, to disaggregate results for individual companies and enable an investigation of areas in which they can improve – informed by TFP constituents. This study contributes to the current body of literature by utilising a method not widely applied in the water sector to assess the optimal routes to measure efficiency in a holistic sustainability context. Additionally, it provides an insight to TFP change and potential avenues for improvement for UK WaSCs and the sector as a whole. The findings and methods are of use to water company decision-makers and regulators, allowing identification of areas of improvement, effectiveness of their operations and potential collaborators for sharing of best practice.

5.2. Methodology

5.2.1. The Hicks-Moorsteen Productivity Index

The Hicks-Moorsteen Productivity Index is defined as a ratio of aggregate output quantity over aggregate input quantity index (Bjurek *et al*., 1998). A major advantage of HMPI over other productivity methods is that a choice between input or output orientation is not required since the approach conducts a simultaneous orientation of input and output. This is due to the combination of output and input quantity indices using the Shephard output and input distance functions (O'Donnell, 2011).

Under the assumption of each WaSC using a vector of *M* inputs x (x_1, x_2, …, x_M) to produce a vector of *S* outputs y = (y_1, y_2, …, y_S), the output and input distance functions are defined thus (Shephard, 1953):

$$D_t^o\ (x,y) = \min_{\delta} \{\delta > 0 : \left(x, {}^{y}/_{\delta}\right) \varepsilon T^t\} \tag{5.1}$$

$$D_t^i\ (x,y) = \min_{\rho} \{\rho > 0 : \left({}^{x}/_{\rho}, y\right) \varepsilon T^t\} \tag{5.2}$$

Where T^t denotes production possibilities set at period-t. D_t^o (x, y) symbolises the output distance function and evaluates the inverse of the largest radial expansion of the output vector, which is achievable, given the input vector. Conversely, D_t^i (x, y) denotes the input distance function and evaluates the largest radial contraction of the input vector attainable while fixing the output vector (Epure *et al*., 2011).

For a base period t, Bjurek et al. (1998) defined HMPI as:

$$HMPI_{T\ (t)}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{[D^o_{T(t)}(x^t,y^t)/D^o_{T(t)}(x^t,y^{t+1})]}{[D^i_{T(t)}(x^t,y^t)/D^i_{T(t)}(x^{t+1},y^t)]} \tag{5.3}$$

For a base period $t+1$, HMPI is defined as:

$$HMPI_{T\ (t+1)}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{[D^o_{T(t+1)}(x^{t+1},y^t)/D^o_{T(t+1)}(x^{t+1},y^{t+1})]}{[D^i_{T(t+1)}(x^t,y^{t+1})/D^i_{T(t+1)}(x^{t+1},y^{t+1})]} \tag{5.4}$$

A geometric mean of the HMPI for base period t and $t+1$ yields:

$$HMPI_{T(t),\ T(t+1)}\ (x^{t+1}, y^{t+1}, x^t, y^t) =$$
$$[HMPI_{T(t)}(x^{t+1}, y^{t+1}, x^t, y^t)\ \times\ [HMPI_{T(t+1)}(x^{t+1}, y^{t+1}, x^t, y^t)]^{1/2} \tag{5.5}$$

An asset of HMPI is its classification into technical potential (TECH) and relative efficiency (TFPE) change, along with breakdown of TFPE into various components. TECH indicates a shift in the efficiency production frontier, advancements of which illustrate expansion in production possibilities (Fare and Grosskopf, 1996). TFPE measures the movement of units (WaSCs) away or towards production frontier and is regarded as a catching up index (Maziotis *et al.*, 2015). The indication being that TFPE involves the capacity of WaSCs to be managed with the best operational and corporate practices. TFP then, is the product of TECH and TFPE (O'Donnell, 2011):

$$TFP_{it} = TECH_{it} \times TFPE_{it} \tag{5.6}$$

O'Donnell (2008) devised the breakdown of TFPE into its drivers, using two production frontiers as references. The first, mix-restricted production frontier has the output or input sets held fixed. The second is the unrestricted production frontier, which has variable output and input sets. Established on these two frontiers, whilst under an input-orientation, the sub-indices for TFPE are defined by O'Donnell (2014) in Table 5.1.

Table 5.1. *Descriptions and explanations to the sub-indices of total factor productivity efficiency change, adapted from the works of O'Donnell (2008) and O'Donnell (2014).*

TFPE sub-indices	Description
Input-oriented Technical Efficiency (ITE)	Measures the difference between the observed and maximum TFP possible, while keeping the input mix, output mix and output level fixed. This concept is exhibited in Figure 5.1, where the curve passing through points B and D is the frontier of a mix-restricted production possibilities set. The production possibilities set is mix-restricted in the sense that it only contains input and output aggregate vectors that can be written as scalar multiples of the input and output vectors at point A. ITE is thus a measure of the difference in TFP at points A and B: $ITE_0 = \tan a / \tan b$.
Input-oriented Scale Efficiency (ISE)	Assesses the difference between TFP at a technically efficient point and maximum TFP possible while holding the input and output mixes fixed but allowing the amounts to change. This measure of efficiency is represented in Figure 5.1 as a movement from point B to point D: $ISE_0 = \tan b / \tan d$.
Residual Mix Efficiency (RME)	Evaluates the contrast between TFP on a mix-restricted frontier point and maximum TFP possible when input and output mixes (and levels) can vary. This is illustrated in Figure 5.1 as a movement from point D to point E: $RME_0 = \tan d / \tan e$. The curve passing through E is the frontier of an unrestricted production possibilities set (unrestricted meaning there are no restrictions on input or output mix). The term "mix" refers to the movement from point D to E, where a movement from an optimal point on a mix-restricted frontier to an optimal point on a mix-unrestricted frontier occurs, therefore the difference in TFP is essentially a mix-effect. The term "residual" is used here because i) this movement may also involve a scale change ii) when comparing TFP at point A with TFP at the point of maximum productivity (point E), RME is the component that remains after accounting for pure technical and scale efficiency effects.
Input-oriented Mix Efficiency (IME)	Analyses the distance between TFP at a technically efficient point on the mix-restricted frontier and the maximum TFP possible, while the output level is fixed. This measure of efficiency is depicted in Figure 5.1 as a movement from point B to U: $IME_0 = \tan b / \tan u$.
Residual Input-oriented Scale Efficiency (RISE)	Determines the difference between TFP at a technically and mix-efficient point and TFP at the point of maximised productivity. The term "scale" is used to reflect the fact that any movement around an unrestricted production frontier is a movement from one mix-efficient point to another, so any improvement in TFP is essentially a scale effect. The term "residual" is also used since even though all the points on the unrestricted frontier are mix-efficient, they could still have different input and output mixes. Therefore, what is essentially a measure of scale efficiency may contain a residual mix effect. Residual is further appropriate as term here because when decomposing the difference between TFP at the observed point A and TFP at the point of maximum productivity E, the residual scale efficiency is the component that remains after accounting for pure technical and pure mix efficiency effects. RISE is exhibited in Figure 5.1 as a movement from point B to U: $RISE_0 = \tan u / \tan e$.

The TFPE is represented in Figure 5.1 as a movement all the way from point A to point E, measured as the difference between observed TFP and maximum TFP. The relationship with its components are simplified here:

$$TFPE_{it} = ITE_{it} \times IME_{it} \times RISE_{it} \tag{5.7}$$

$$TFPE_{it} = ITE_{it} \times ISE_{it} \times RME_{it} \tag{5.8}$$

A HMPI >1 indicates an increase in TFP, <1 illustrates a decline in TFP, a result of exactly 1 demonstrates there was no change in TFP.

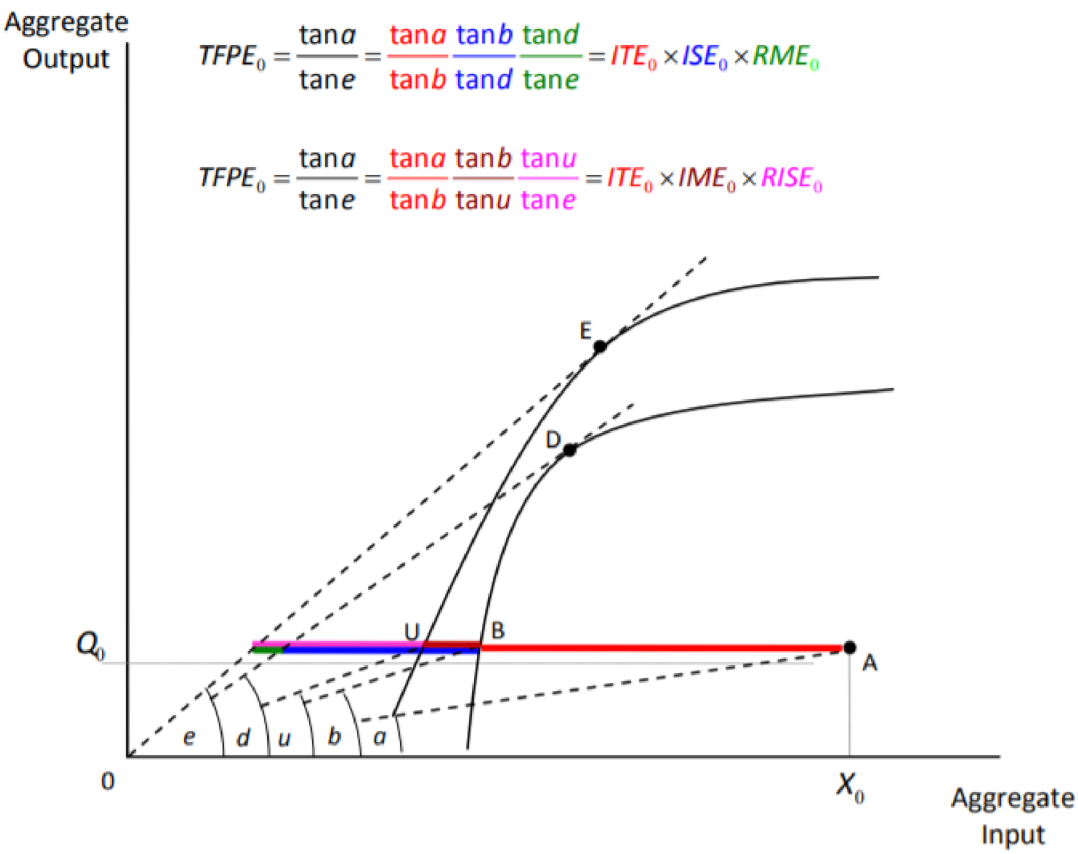

Figure 5.1. *An input-oriented decomposition of TFPE sourced from O'Donnell (2014). Q represents outputs, X depicts inputs, A is observed TFP point, E is maximum productivity, D is the optimal point on a mix-restricted frontier, B portrays the technically efficient point on the mix-restricted frontier, and U illustrates the maximum TFP possible when output levels are fixed. Further details are within Table 5.1.*

To compute output and input distance functions, and therefore HMPI, there are two approaches, parametric and non-parametric methods. Of the parametric methods, stochastic frontier analysis (SFA) is the most widely used. The advantage of SFA is that it explains random statistical noise and can account for the effects of errors in the data (Parmeter and Zelenyuk, 2019). The limitation is that parametric techniques require strong assumptions of the functional form (Moutinho *et al*., 2020). Conversely, non-parametric methods such as data envelopment analysis (DEA) use mathematical programming and thus do not need specification of the functional frontier (Silva *et al.,* 2017). This is the main advantage over SFA and outweighs DEA's limitations of assuming there are no atypical data observations, making it vulnerable to outliers and errors (Cooper *et al*., 2006). Due to the advantages DEA offers, and following O'Donnell (2011), Medal-Bartual *et al*. (2016), and Molinos-Senante *et al*. (2016), this study utilises DEA to compute HMPI. The input and output distance functions were computed in 'R', a statistical computing software with the package 'productivity' created by Dakpo *et al*. (2018).

5.2.2. Data description

The sample consisted of 12 WaSCs from across the UK, with annual data over the period 2013-2018. To justly represent the key operations of WaSCs, the choice of inputs and outputs is pivotal. To investigate the various approaches to analysing efficiency, different configurations of inputs and outputs were evaluated and the justifications for their use are outlined in Section 5.3.1. The inputs used were *operational expenditure* (*OPEX*) and *total expenditure* (*TOTEX*), whereas the diversified outputs were *water supplied and wastewater treated* (combined), *self-generated renewable energy*, *leakage reduction*, *consumption per capita reduction*, and *customer satisfaction*, which is measured by a service incentive mechanism (SIM) score out of 100, deployed by OFWAT. *Leakage reduction* and *consumption per capita reduction* were converted to non-negatives to allow the computation to proceed without errors; this was completed by bringing the largest negative up to a value of one, then adding the difference from the negative value to one, to all other values. All of the data was acquired from company annual reports and is summarised in Table 5.2.

The size of the sample, when using DEA, is required to satisfy a minimum size threshold to bypass relative efficiency discrimination issues. 'Cooper's rule' is used to gauge this size threshold, and specifies the quantity of units must be ≥ max$\{m\ x\ s; 3(m+s)\}$ where m represents inputs and s represents outputs (Cooper *et al*., 2007). The maximum inputs and outputs used in any variable configuration in this study comprised of one input and three outputs, therefore Cooper's rule was followed. Furthermore, one of the advantages of DEA is regarded to be its appropriateness with smaller sample sizes (Arjomandi *et al*., 2015).

Table 5.2. *Summary statistics for the six-year period (2013-2018) analysed for UK WaSCs.*

		Average	SD	Minimum	Maximum
Inputs	Total expenditure (million£)	863	506	288	2,724
	Operational expenditure (million£)	504	320	143	1,214
Outputs	Water supplied and wastewater treated (Ml/day)	2,613	1,763	725	7,102
	Self-generated renewable energy (GWh)	98	89	2	387
	Customer satisfaction (SIM score)	82	5	68	90
	Leakage reduction (Ml/day)	54	12	1	89
	Consumption per capita reduction (l/h/day)	11	4	1	22

5.3. Results and Discussion

5.3.1. An enquiry into efficiency analysis

Evaluating the efficiency of water companies can take many forms, with hundreds of indicators available to choose from (Berg, 2013). However, in TFP analysis with frontier techniques like DEA and SFA, a limited core number of variables are often chosen, since including the majority of possible variables is not feasible (Worthington, 2014). Variations of core indicators are evaluated and their appropriateness is discussed relative to capturing the key operations and responsibilities of water companies in relation to wider sustainability objectives. This was conducted through eight repeats of the HMPI model, each with different configurations of variables, enabling the exploration of the importance of variable selection when assessing productivity. The breakdown of each individual model repeat, including all constituents of efficiency and individual company efficiency scores for each year are available in the Supplementary Information.

The most common variable approach to efficiency analysis of water companies in the literature comprises of including *OPEX* and *capital expenditure* (*CAPEX*) as inputs, and the volume of *water supplied and wastewater treated* as outputs, whether that is within a single year analysis or a multi-year evaluation within productivity (Zschille and Walter, 2014; Maiotis *et al*., 2015; See, 2015). This configuration of inputs and outputs therefore made up the first model run (T-W in Table 5.3), displaying an average increase in TFP of 0.86%, solely as a result of efficiency increase. This slight increase was anticipated as the mature UK market continues to optimise total spending, as supported by Portela *et al*. (2011) who showed significant productivity improvements between 1994-2005 using a meta-Malmquist index, before it dropped off until 2007. Molinos-Senante and Maziotis (2020b) published a similar result using a normalised quadratic function, illustrating that the sector increased its productivity annually by 6.1% within 1993-2016. The TFP increase however did contradict further TFP studies of the UK with similar indicators to T-W. Molinos-Senante *et al*. (2017a) used the Färe-Primont Productivity Index and concluded productivity declined by 7.2% during 2001-2008, whilst Molinos-Senante *et al*. (2014b) showed the productivity of the UK water industry from 2001 to 2008 reduced by 11.5% and 12.9% when using the LPI and MPI, respectively. The disparity between studies is likely due to differing sample years, methodologies, and the sample itself, since some studies included the whole of the UK and others just England and Wales, some studies also contained water only companies and WaSCs, whilst others just WaSCs. Although this change in sample size is not large, it can be significant when the original sample size is small as is the case within the UK (Zhang and Bartels, 1998). The drawback to the T-W variable configuration is that it does not capture other elements that a water company provides and for which it is responsible.

Table 5.3. *Summarised TFP, TFPE and TECH* change of various variable configurations for UK water and sewage companies for 2014-18. Average changes are based on the mean percentage changes for all years and for all companies.*

Model	Inputs	Outputs	dTFP average	dTECH average	dTFPE average
T-W	TOTEX	Water supplied and wastewater treated	+0.86%	-0.39%	+1.37%
T-WRC	TOTEX	Water supplied and wastewater treated, renewable energy generation, customer satisfaction	+1.82%	-0.01%	+2.06%
T-RC	TOTEX	Renewable energy generation, customer satisfaction	+2.35%	-1.24%	+3.91%
T-LC	TOTEX	Leakage reduction, consumption per capita reduction	+4.86%	+0.29%	+5.14%
O-W	OPEX	Water supplied and wastewater treated	-3.15%	-3.85%	+0.79%
O-WRC	OPEX	Water supplied and wastewater treated, renewable energy generation, customer satisfaction	-1.15%	-2.43%	+2.06%
O-RC	OPEX	Renewable energy generation, customer satisfaction	-0.90%	-2.78%	+2.85%
O-LC	OPEX	Leakage reduction, consumption per capita reduction	+1.22%	-2.41%	+5.58%

**TFP is total factor productivity; TECH is technical change; TFPE is efficiency change*

Customer satisfaction and *self-generated renewable energy* were identified as key indicators to incorporate into the analysis, which along with the T-W variables (Table 5.3), make up T-

WRC. *Customer satisfaction* was selected as it is the ultimate measure of success for a utility provider and, representing social aspects of sustainability, is a fundamental parameter for companies to prosper and avert regulatory sanctions. The more environmentally focussed *self-generated renewable energy* was chosen since water companies are a major consumer of energy, as noted in Section 5.1. Therefore, reducing their impact on the national grid supply and the associated greenhouse gas emissions is a responsibility that is incorporated into the second variable configuration. T-WRC resulted in a larger TFP increase of 1.82% between 2014 and 2018, compared to T-W, again due to the increases in TFPE. The progress relative to T-W was expected since *customer satisfaction* and *self-generated renewable energy* consistently increased throughout the sample period by 1.24% and 28% on average year-on-year, respectively. Although T-WRC does cover more operational outputs for water companies, it has a limitation in the form of the main service output indicator: *water supplied and wastewater treated*. Water companies have been tasked to reduce leakage in their supply network by 15% by 2025, and 50% by 2040 (EFRA, 2018) to help future-proof themselves against climate change, which could reduce the availability of abstraction water (Dallison *et al*., 2020; Gov.UK, 2020a), and to better manage water resources. Companies take active measures to do this by investing in leakage reduction and conducting education campaigns to reduce consumption; e.g., Manouseli *et al.* (2019) showed active users within such schemes reduced their consumption by approximately 15%. Therefore, having *water produced and wastewater treated* as outputs in a TFP model may mask efficiency by treating higher water consumption, and lower investment in consumption (leak) reduction, as efficient. This would inaccurately portray companies that have invested in leakage reduction and public campaigns to consume less water as being less efficient.

Thus, to avoid this potential distortion, the T-RC model consisted of *renewable energy self-generation* and *customer satisfaction* as the outputs, whilst keeping *TOTEX* as the input. This displayed a TFP increase of 2.35% between 2014 and 2018, with an increase of 3.91% for TFPE. To explore more areas that companies are prioritising and attempting to improve upon, T-LC has *leakage reduction* and *consumption per capita reduction* as outputs. Typically, *consumption per capita* is not considered an output within evaluations of water companies however, since it has been shown that companies can influence it, it is included here. This variable configuration resulted in the largest average TFP increase between 2014 and 2018 of 4.86%, which, along with showing how companies have improved more holistically, also exemplifies how efficiency analysis with *water supplied and wastewater treated* as an output could distort results with respect to sustainable business objectives. Collectively, models T-RC and T-LC demonstrate how much WaSCs in the UK have improved non-economic aspects of sustainability between 2013/14-2018/19.

The first four models were all calculated with *TOTEX* as an input, however, CAPEX being a part of this input had the potential to skew results as the benefits of capital investments are often not shown immediately (Abbott and Cohen, 2009). Model configurations O-W, O-WRC, O-RC and O-.LC therefore were all repeats of the first four variable configurations, but contained just *OPEX* as their inputs. As Table 5.3 illustrates, the *OPEX* versions of the models all resulted in the companies being less efficient compared to the *TOTEX* versions with O-W, O-WRC and O-RC actually presenting negative results, indicating that the sample has declined in efficiency. One possibility for these results is that CAPEX is more efficient than *OPEX* for companies within the sample and subsequently masked its inefficiency within *TOTEX*, however, reductions in CAPEX whilst also improving significantly in *self-generated renewable production* and *leakage reduction* seems unlikely. An alternative possibility is that CAPEX from the time preceding the sample period into the base year was higher to pay for infrastructure represented in outputs in these models such as *leakage reduction*, *renewable energy production* and *customer satisfaction* to a lesser extent. From then, a fall in CAPEX could have followed, so within *TOTEX* as an input, it was low compared to the now increasing outputs brought about by prior spending. If this is the case, then incorporating CAPEX essentially creates efficiency lags that must be accounted for, or at least acknowledged, when drawing conclusions from results. To evade this potential efficiency lag, studies with a sample over a longer period could adopt a five-year rolling average, since shorter periods could generate perverse incentives to cut investments in the short term if the efficiency lag is not considered in the research outputs. Some studies opt to include length of water mains as a proxy to represent capital (De Witte and Marques, 2010a; Ananda, 2014; Molinos-Senante *et al.,* 2018a), which negates the issue raised here however, that comes with its own issues of accuracy when acting as a proxy as demonstrated by Walker *et al*. (2020). Whilst these results have been attempted to be explained by the role of CAPEX, there are the direct ramifications of *OPEX* too. Inflation rate increased at an average of 1.7% per year over the sample period (Office for National Statistics, 2020a) and the energy price index also raised by an average of 3.19% per year for electricity and 8.44% for gas (Gov. UK, 2020b). Furthermore, the water retail price index increased by an average of 2.44% during the same period (Office for National Statistics, 2020b). These statistics combined likely had at least a small impact on the relatively lower productivity compared to *TOTEX* and further highlights the advantages of companies producing their own renewable energy.

The assorted inputs and outputs for the model variable configurations yielded changes in perceived productivity for the whole water sector. As Table 5.4 shows, company-level TFP also fluctuated. There was a disparity between the first four that used *TOTEX* as the input and the last four models that used *OPEX* as the input, which was seen in the overall sector trends in Table 5.3, too. For example, companies 7 and 8 were ranked 2nd and 1st in the majority of the *TOTEX* models, but dropped to below average and alternate between 4th and 5th in the *OPEX* models, respectively. Furthermore, company 12 went from generally below average rankings in the *TOTEX* models, with exception of model T-LC where it ranked 2nd, to ranking 1st in the latter four models. Company 9 appears to have fallen behind when the more sustainability-orientated indicators were introduced. It ranked 4th in T-W however, dropped to 10th-12th in models T-WRC, T-RC and T-LC when indicators such as *self-generated renewable energy*, *customer satisfaction*, *leakage reduction* and *consumption per capita reduction* were implemented. This trend was then replicated in the *OPEX* models, although to a lesser extent.

Company 5 performed poorly throughout whether that was using *OPEX* or *TOTEX* as the input, suggesting that they have neglected all aspects of sustainability relative to the other companies and have held back the TFP progress for the whole sample. These results collectively show how choosing the correct variables to represent a specific desired objective is critical and how small variations in variable selection or definition could significantly skew benchmarking attempts. A larger sample would have enabled more indicators to be evaluated, giving a more holistic representation of sustainability however, with the limited indicators allowed by the sample, key sustainable parameters are included in this study.

Table 5.4. *Ranking 12 WaSCs for the eight model variable configurations, based on the TFP scores.*

Company	Total Factor Productivity (TFP) Rankings							
	T-W	**T-WRC**	**T-RC**	**T-LC**	**O-W**	**O-WRC**	**O-RC**	**O-LC**
1	8th	7th	8th	5th	11th	11th	11th	5th
2	12th	11th	10th	8th	6th	7th	8th	2nd
3	9th	5th	3rd	6th	8th	8th	3rd	6th
4	3rd	3rd	5th	4th	10th	10th	10th	3rd
5	11th	12th	11th	10th	12th	12th	12th	12th
6	6th	6th	6th	11th	7th	2nd	2nd	11th
7	2nd	2nd	2nd	3rd	9th	9th	7th	8th
8	1st	1st	1st	1st	4th	5th	5th	4th
9	4th	10th	12th	12th	2nd	4th	9th	10th
10	5th	4th	4th	7th	3rd	3rd	4th	7th
11	10th	9th	9th	9th	5th	6th	6th	9th
12	7th	8th	7th	2nd	1st	1st	1st	1st

5.3.2. Water market efficiency over time

The model variable configuration to analyse the TFP change of UK WaSCs in the following sections was model T-WRC in Table 5.3. T-WRC was selected because it included key indicators that cover all aspects of sustainability. *TOTEX* was incorporated as it was deemed that CAPEX should be represented because ultimately, it is an important component of company spending that can be associated with significant (lagged) technical efficiency and sustainability improvements. Furthermore, the UK water sector now actively reports under *TOTEX*, with the regulator OFWAT (2018b) commenting that the switch to *TOTEX* has removed a regulatory barrier, enabling additional efficiencies and innovation. Any potential time lags in efficiency results are a limitation of the research in the upcoming sections but will be appreciated within the enquiry of the results. *Water supplied and wastewater treated* was chosen as it is the main service output of water companies, representing their whole reason for operating, therefore analysing efficiency without it cannot be considered holistic sustainability or otherwise.

Despite the limitations to some of the indicators discussed in Section 5.3.1, they are the most appropriate grouping considering the data available and sample size; furthermore, the results still give a good indication of how companies are performing within a more comprehensive sustainability efficiency assessment. Productivity change was deemed to increase when TFP and constituent scores were >1 and to decrease when estimates were <1.

The average TFP change was positive with a value of 1.018 over the sample period as shown in Table 5.5, which indicates an average increase in productivity of 1.8%, however, this was the consequence of 2015/16 having a large TFP estimate compared to other years of 1.23 (23%). The increase was large enough for the overall average productivity change to be positive, despite all other years displaying a decline in TFP. This was unexpected as 2015 was the beginning of the five-year cycle consisting of asset management plan 6, which was to be a period of increased investment (OFWAT, 2014), however, the year displayed a *TOTEX* decline of 13.17% compared to the previous year, whereas increased spending followed in the next four years. It is likely that the *TOTEX* decline in 2015 was a major driver of the increased efficiency, although *self-generated renewables* increased by 20.62%, whilst *customer satisfaction* improved by 1.02% and *water supplied and wastewater* treated declined by 1.95%. The limitation of confining productivity results to yearly values as opposed to extended blocks of time is exemplified here, but is applied in this research and many other pieces of work due to the limited temporal sample range. A larger increase in TFP was anticipated due to the inclusion of *self-generated renewable energy* as an output, since this increased dramatically in the sample period (28% average year-on-year). It is possible that the renewable energy increase masked some other inefficiency, which appears to be the case when examining model T-W within Table 5.3. This mix of variables displayed a TFP average increase of 0.86%, whilst containing *TOTEX* as the input and *water supplied and wastewater treated* as the output. This was approximately 1% lower compared to the more holistic model variable configuration used in this section, indicating *customer satisfaction* and *self-generated renewable energy production* attributed to increased TFP. Another reason the increase was not as large as anticipated appeared to be a result of *TOTEX* increasing nearly as much as their outputs during the sample period, with an average year-on-year increase of 3.01%. These combined with the limitations in using *water supplied and wastewater treated* as an output discussed in Section 5.3.1 likely limited larger TFP increases. Ultimately, there was a positive average TFP change and this should be viewed favourably, especially when companies are improving renewable energy generation and customer service, in addition to the core operations of providing high standards of drinking water and treating wastewater responsibly.

Table 5.5. *Summarised TFP change and its components* for UK water and sewage companies.*

Year	dTFP	dTECH	dTFPE	dITE	dISE	dRISE	dRME
2014/15	0.996	0.995	1.002	1.091	0.935	0.925	0.993
2015/16	1.230	1.057	1.176	0.987	1.036	1.194	1.158
2016/17	0.952	0.945	1.006	0.936	1.053	1.088	1.031
2017/18	0.945	0.958	0.987	1.026	1.004	0.968	0.965
2018/19	0.969	1.044	0.931	0.990	1.007	0.941	0.935
Average	1.018	1.000	1.021	1.006	1.007	1.023	1.017

**TFP is total factor productivity; TECH is technical change; TFPE is efficiency change; ITE is input-oriented technical efficiency; ISE is input-oriented scale efficiency; RISE is residual input-oriented scale efficiency; RME is residual mix efficiency.*

The main driver of the TFP positive change was TFPE, which averaged at 2.1%, whilst TECH remained at an unchanging 1. The indication being that from 2014-18, the production frontier remained at the same level, however, companies on average have moved 2.1% closer to the frontier. This was again largely due to 2015/16, which displayed an increase in TFPE of 17.6%, outweighing the decreases in the last two years of 1.3% and 6.9%, illustrated in Figure 5.2. The findings suggest that capital investment remained steady relative to increased outputs during the sample years, whereas management of infrastructure and resources improved marginally. Therefore, to improve TFP, WaSCs must invest more in impactful capital projects compared to their 9.15% year-on-year average reduction, if they are to improve the outputs used in the mode further; these solutions could be updated technologies at treatment plants, renewable energy installations, and extra customer-facing staff capacity. The extra capital enterprises may then allow the expert personnel that increased TFPE to propel efficiency on even more. Since the CAPEX decline at least partially drives positive efficiency here, it is possible that in future years there could be a negative legacy effect, where future efficiency evaluations show a decline because of their higher spending relative to the period covered in this study.

An advantage of the HMPI is that TFPE can be split up into component parts. A WaSC is deemed efficient if it has an ITE score of one as this indicates the company is on the efficient production frontier, less than one and it is under the frontier and inefficient. A company with an ITE score equal to one, whilst displaying a RISE of less than one, remains on the efficient production frontier however, it is considered relatively unproductive. Table 5.5 displays that ITE increased marginally by 0.6% on average, while RISE increased by 2.3%, showing both technical efficiency and scale efficiency components positively contributed to TFPE. Further constituents of TFPE namely, ISE and RME both on average increased by 0.7% and 1.7%. The scale efficiencies imply the UK water sector is moving closer to its technically optimal scale in regards to output. In 2015/16, the largest TFP and TFPE changes of +23.0% and +17.6% occurred, respectively, had a negative ITE score of 1.3%. Despite this, large productivity gains in RISE and RME of 19.4% and 15.0% ensured the year had such a large TFP increase. Collectively, these results suggest that economies of scale and scope contributed positively to the TFPE result, allowing WaSCs to move to closer the efficiency frontier by improving in diversified outputs and optimising treatment plant sizes relative distribution area.

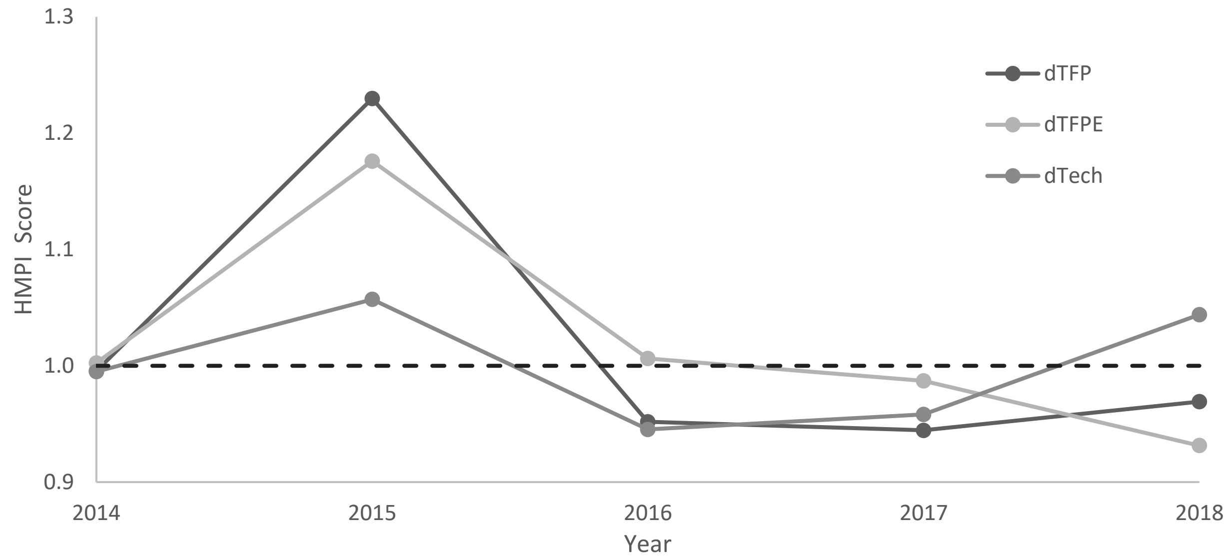

Figure 5.2. *The change in total factor productivity (TFP), TFP efficiency change (TFPE) and TFP technical change (TECH) for all UK water and sewage companies as a collective for 2014-2018.*

5.3.3. Company-level efficiency over time

Figure 5.3 displays that exactly half of the sample exhibited a positive TFP value, furthermore the TFP standard deviation was 0.043 (Table 5.6), indicating that the sample was relatively homogenous. This was expected to an extent since the UK has a mature water market, having been consolidated after the Second World War then eventually privatised in 1989 and regulated strictly ever since (OFWAT, 2020c). The largest TFP gains were from company 8, which had increased productivity by 10.9%.

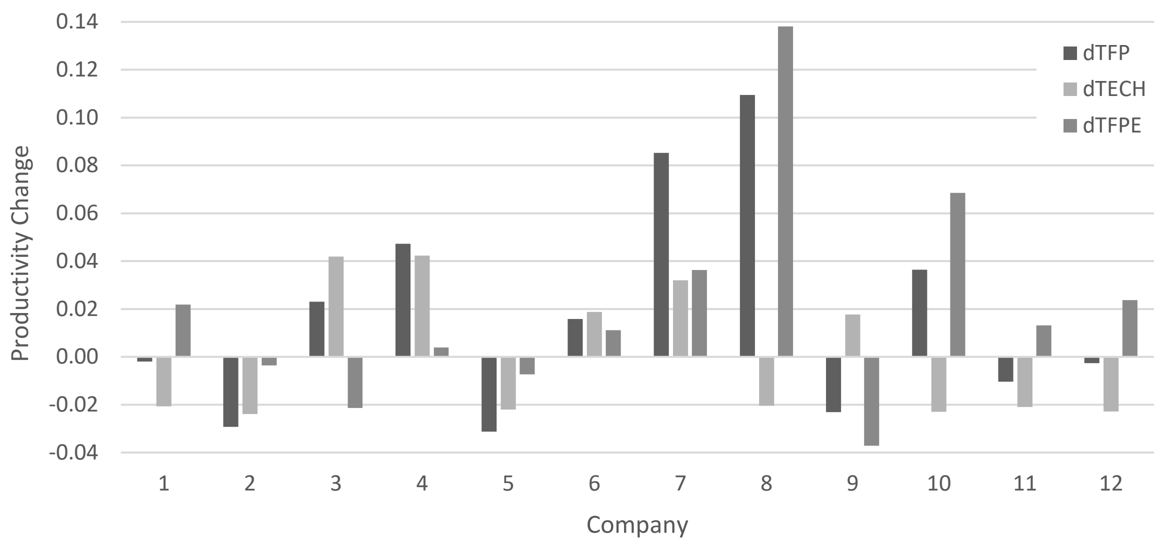

Figure 5.3. *The change in total factor productivity (TFP), TFP efficiency change (TFPE) and TFP technical change (TECH) for all individual UK water and sewage companies for 2014-2018.*

Table 5.6 shows that the increase was due to a large increase in TFPE of 13.8%, suggesting that the management of existing resources during this period significantly improved, although this is likely also due to capital projects from before the sample period coming online. Conversely, company 5 had the largest average decline in TFP during 2014-18 of -3.1%, struggling slightly more through optimising capital investment than through the management of resources. Companies 5 and 8 did have an almost identical average TECH decline, showing effective capital investment of the most improved company was as poor as the worst performing company. This conveys that company 8 can still considerably improve, despite being the top performer. It should be noted that not all companies necessarily operate in equal conditions, with exogenous factors such as rurality, water source and *population density*, to just name a few factors, all affecting their efficiencies (Walker *et al*., 2019). Although each company will have slightly different operational and corporate conditions, this exemplifies where communication and sharing of best practices can dramatically improve productivity. The current limitation to this is that the UK sector is privatised, and many efficiency gains are made through ‘commercially sensitive’ means.

The operational conditions within the UK are fairly uniform however, even minor variances in certain factors can affect renewable energy feasibility for companies, influencing their financial and energy payback times (Murphy and McDonnell, 2017). For example, wind speed averages and peaks are much higher in coastal areas and the north of the UK, ranging from an average 5-13 m/s in 1981-2010, whereas inland and in the south largely averages at 1.5-2.6 m/s (Met Office, 2020). A further example is in solar irradiance; Burnett *et al*. (2014) converted gridded sunshine duration to solar irradiance in order to map it for the UK within 1961-1990, which showed the south for average annual irradiance ranged from 90.9 to 126 Wm^{-2}, whilst the north had a range of 71.8-107.1. Additionally, topographical gradients vary throughout the whole of the UK (Topographic map, 2020), significantly altering the dynamics and viability of recovering energy from hydropower (McNabola *et al*., 2014). The one major renewable energy source that is uniform for all the companies in the sample is the production of biogas from wastewater, although the quantities will differ depending on populations, and transport distance (and associated costs) to centralised plants will vary with population densities (cities vs. rural, etc.). A further major barrier to renewable energy projects is land cost, which has disparities within the UK, generally being cheaper in the north and the south (Hall and Tewdwr-Jones, 2019). Collectively, this means generating renewable energy within the UK is not equal for each water company; therefore, future efficiency studies could enhance their analysis by considering this, perhaps integrating a ‘percentage of possible renewable energy utilised’ based on natural resources and economic thresholds.

Table 5.6. *Average TFP change and its components* for UK water and sewage companies 2014-18.*

Company	dTFP	dTECH	dTFPE	dITE	dISE	dRISE	dRME
1	0.998	0.979	1.022	1.012	1.019	1.045	1.038
2	0.971	0.976	0.996	0.978	1.004	1.029	1.023
3	1.023	1.042	0.979	1.000	1.000	0.979	0.979
4	1.047	1.042	1.004	1.000	1.000	1.004	1.004
5	0.969	0.978	0.993	0.956	0.995	1.037	1.047
6	1.016	1.019	1.011	1.000	1.000	1.011	1.010
7	1.085	1.032	1.036	1.000	1.033	1.036	1.003
8	1.109	0.980	1.138	1.080	1.027	1.077	1.046
9	0.977	1.018	0.963	0.997	0.999	0.966	0.967
10	1.036	0.977	1.068	1.033	1.005	1.025	1.017
11	0.990	0.979	1.013	0.994	0.998	1.029	1.028
12	0.997	0.977	1.024	1.025	1.005	1.041	1.037
Average	1.018	1.000	1.021	1.006	1.007	1.023	1.017
SD	0.043	0.027	0.044	0.029	0.012	0.029	0.024

***TFP is total factor productivity; TECH is technical change; TFPE is efficiency change; ITE is input-oriented technical efficiency; ISE is input-oriented scale efficiency; RISE is residual input-oriented scale efficiency; RME is residual mix efficiency.*

Technical change improved for five out of twelve WaSCs, with companies 3 and 4 leading with the way, improving by 4.2% each. This means that these companies have advanced regarding their technological condition, a probable result from long-term strategic planning and capital investment. However, when assessing the *TOTEX* year-on-year average, it was evident for these WaSCs that their change in spending was modest and comparable to their peers, increasing by 2.53% and 4.72%, respectively. This shows the difficulty in analysing the efficiency of *capital expenditure* as discussed in Section 5.3.1. It should, however, be noted that the efficiency is in relevance to the outputs, and so it is probable that their capital spending was more optimised than other companies in the sample. Concerning efficiency change, eight out of twelve companies progressed their operational systems and procedures, with company 8 improving by 13.8%, the most of all the WaSCs.

The components of efficiency change, which are displayed in Table 5.6, can offer even more of an insight into productivity. As the previous section noted, an ITE score of 1 indicates the WaSC is on the production frontier, whilst a score of less than 1 for RISE categorises the WaSC as relatively unproductive. Eight companies (66%) displayed an ITE score of 1 or higher and therefore positively shifted the efficiency production frontier or remained on it. Although these improvements were observed, company 3 still reduced in TFPE due to it remaining relatively unproductive, as indicated by the decline in RISE. Only two companies, 3 and 9 did not match the overall positive trend for RISE and RME, whilst just companies 5, 9 and 11 presented negative results for ISE. This indicates that the majority of UK WaSCs had positive economies of scale and scope with TFP largely being driven by improved operational practices of existing infrastructure and resources. Although collectively the progress of TFP, TFPE and its constituents were small, continuing to improve in an already largely efficient sector is positive, especially within a framework evaluating more holistic sustainability outputs. Individual analysis at this scope further highlights how sharing best practice between the companies featured on different ends of the various components of TFP results could be advantageous, with lessons being relevant for companies outside of the region, too.

5.4. Conclusions

The objectives of this research were to utilise the Hicks-Moorsteen Productivity Index as a framework to evaluate the efficiency (as temporally applied TFP) of water service companies in the UK between 2013 and 2018, exploring the influence of input and output indicator selection on the representation of critical sustainability outcomes. In addition to more traditional indicators such as *TOTEX* and *Water supplied and wastewater treated,* the following indicators of sustainable performance were used: *self-generated renewable energy, customer satisfaction, leakage reduction, and per capita consumption reduction,* which were interchangeably utilised within eight model variable approaches. The study showed novelty by applying and comparing a mix of indicators across the sustainability spectrum, particularly poignant within the computation of the seldom-used HMPI on a UK sample of water companies. The choice of variables had a major influence on the ranking and perceived operational efficiency among WaSCs. CAPEX (used as part of *TOTEX*) for example, is an important input for tracking company operations however; possible associated efficiency benefits can lag investment, leading to apparent poor short-term performance following capital spending. A solution is to benchmark over longer periods where possible, implementing a 5-year rolling average or similar. Furthermore, *water supplied and wastewater treated* was deemed an unconstructive output from a sustainability perspective since it contradicts efforts to improve sustainability through reduced *leakage* and *consumption per capita*. Alternatives should be assessed in future research; possible options are *Customer satisfaction* and water quality measures. Despite these limitations, *TOTEX and water supplied and wastewater treated* were used alongside *customer satisfaction* and *self-generated renewable energy* for a holistic sustainability assessment that captures decisive company activities within a small sample. They indicated the UK water sector has improved in productivity by 1.8% on average for 2014-18 and still had room for improvement, as a technical decline was evident for both the best and worst performers. Collectively the sample's production frontier was unchanged but on average companies moved 2.1% closer to it, and further decomposition of productivity revealed this was due to improvements in economies of scale and scope with residual input-oriented scale efficiency and residual mix efficiency expressing increases of 2.3% and 1.7%, respectively. Careful selection of appropriate input and output variables, integrated within an appropriate productivity framework, is critical to align with sustainability objectives and to target future investment and regulation within the water sector. The largest limitation within this study was the small sample size, which restrained the quantity of indicators that could be used however, core sustainability indicators were still included and future studies can build upon this, particularly within the framework of the HMPI as was successfully applied here. Collectively, these outcomes can contribute to implications on policy, regulation, water management, and future research through displaying a process to assess the optimal routes to measure efficiency in a holistic sustainability context, enabling identification of areas of improvement, effectiveness of their operations, and potential collaborators for sharing of best practice.

6. Pitfalls in international benchmarking of energy intensity across wastewater treatment utilities

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Abstract

The collection, treatment and disposal of wastewater is estimated to consume more than 2% of the world's electrical energy, whilst consumption and wastewater treatment plants (WWTPs) can account for over 20% of electrical consumption within some municipalities. To investigate areas to improve wastewater treatment, international benchmarking on energy (electrical) intensity was conducted with the indicator kWh/m^3 and a quality control of secondary treatment or better for ≥95% of treated volume. The core sample included 321 companies from 31 countries, however, to analyse regional differences, 11 countries from an external sample made up of various studies of WWTPs was also used in places. The sample displayed a weak-negative size effect with energy intensity, although Kruskal-Wallace analyses showed there was a significant difference between the size of groups (p-value of 0.015), suggesting that as companies get larger; they consume less electricity per cubic metre of wastewater treated. This relationship was not completely linear, as mid to large companies (10,001-100,000 customers) had the largest average consumption of 0.99 kWh/m^3. In the regional analysis, EU states had the largest average kWh/m^3 with 1.18, which appeared a result of the higher wastewater effluent standards of the region. This was supported by Denmark being the second largest average consuming country (1.35 kWh/m^3), since it has

some of strictest effluent standards in the world. Along with direct energy intensity, the associated greenhouse gas (GHG) emissions were calculated. Poland had the highest carbon footprint (0.91 $kgCO_2e/m^3$) arising from an energy intensity of 0.89 kWh/m^3; conversely, a clean electricity grid can affectively mitigate wastewater treatment inefficiencies, exemplified by Norway who emit just 0.013 $kgCO_2e$ per cubic meter treated,despite consuming 0.60 kWh/m^3. Finally, limitations to available data and the analysis were highlighted from which, it is advised that influent vs. effluent and net energy, as opposed to gross, data be used in future analyses. The large international sample size, energy data with a quality control, GHG analysis, and specific benchmarking recommendations give this study a novelty which could be of use to water industry operators, benchmarking organisations, and regulators.

Key words: Wastewater benchmarking; global wastewater energy efficiency; performance analysis, wastewater quality; benchmarking deficiencies

6.1. Introduction

The collection, treatment and disposal of wastewater is a significant consumer of energy, with estimates suggesting that more than 2% of the world's electrical energy is used for water supply and wastewater treatment (Plappally & Lienhard 2012; Olsson 2015). The EU (2017) state that energy requirements in wastewater treatment plants (WWTPs) account for more than 1% of consumption in Europe, whilst Means (2004) and Kenway *et al*. (2019) report that the water network including consumers and WWTPs can consume over 20% of electrical consumption within municipalities. Reducing the energy consumption of wastewater management is integral to efficient resource use within a circular economy and to reduce greenhouse gas (GHG) emissions. This task is more difficult considering WWTP electricity demand within developed countries is expected to increase by over 20% in the next 15 years as controls on wastewater become more stringent (Wang *et al*., 2012; Hao *et al*., 2015); with the same trend expected in developing countries as wastewater quality becomes a greater priority (Lopes *et al*., 2020). The importance of improving the sustainability of wastewater treatment is highlighted by its inclusion in the United Nations Sustainability Development Goal 6 (2021a) that seeks to secure safe drinking water and sanitation, focussing on the sustainable management of wastewater, water resources and ecosystems.

Electric power consumption accounts for approximately 90% of the total energy consumption of WWTPs (Mizuta and Shimada, 2010; Singh *et al.,* 2012). The energy used at each stage of treatment depends on the technologies utilised and the sizes of the plants. Preliminary and primary treatment are estimated to consume between 5-25%, secondary treatment 45-80%, tertiary 10-40%, and sludge 4-14% (Longo *et al*., 2016; Smith and Liu, 2017; Soares *et al*., 2017). Longo *et al*. (2016) detailed the electricity consumption of the different stages of wastewater using data from 21 academic sources (included in the Supplementary Information), which spanned 1-93 case studies per source and covered all sizes of WWTP. Pre-treatment includes the pumping of wastewater, screening, and grit removal and grinding. During this stage, pumping is the only significant energy consumer, at 0.002-0.042 kWh/m^3, depending on the structure and location of the sewer system. Primary treatment involves separating circular settling tanks with mechanical scrapers, using very little electricity ($4.3 \cdot 10^{-5}$ - $7.1 \cdot 10^{-5}$ kWh/m^3). The secondary treatment stage is responsible for a significant proportion of the total electrical consumption, whist the aeration system is the process that consumes most electricity (0.18 and 0.8 kWh/m^3), accounting for 45%-75% of total plant energy consumption (Longo *et al.,* 2016; Gandiglio *et al.*, 2017). Longo *et al*. (2016) comments further that between $8.4 \cdot 10^{-3}$ and 0.012 kWh/m^3 is used by mechanical scrapers in gravity settling to separate sludge. Secondary sludge recirculation requires more pumping, consuming an additional 0.047 to 0.01 kWh/m^3, whilst mixing for anoxic reactors ranges between 0.053 and 0.12 kWh/m^3. Tertiary treatment further increases electricity consumption, the degree to which depends on the technology. Tertiary filtration consumes from $7.4 \cdot 10^{-3}$ to $2.7 \cdot 10^{-3}$ kWh/m^3, UV disinfection uses between 0.045 - 0.11 kWh/m^3, and mechanical utilisation for the dosage of chemicals (e.g., chlorinated reagents, aluminium or iron salts) expends $9.0 \cdot 10^{-3}$ - 0.015 kWh/m^3. Finally, the processing of sludge throughout different stages can represent considerable energy consumption, for example, aerobic sludge stabilisation, which is the most consuming procedure within sludge treatment, can use between 0.024 – 0.53 kWh/m^3.

Efficiency improvements at plant and company level could reduce the energy demand of wastewater treatment. Various methods could enhance overall system intensity, including process-energy reduction and energy recovery from waste, which can be conducted to such an extent that WWTPs can become energy neutral or even energy positive (Maktabifard *et al*., 2018). An effective way to improve efficiency is the use of control engineering techniques (Vrecko *et al.,* 2011). To reduce the complexity of application, costliness and difficulty of access of these techniques, studies such as Nopens *et al*. (2010), Luca *et al*. (2015), and Santin *et al*. (2015) have implemented benchmarking models for the design and testing of control strategies. As approaches become more holistic in terms of sustainability, WWTP performance can improve further, as Barbu *et al*. (2017) noted in their study when analysing the effect of common control actions on performance with indicators covering economics, effluent quality and GHG emissions. Process optimisation techniques such as installing smart meters and control systems for optimal aeration and pumping conditions have also proved affective techniques, with the Electric Power Research Institute estimating that 10-20% of energy savings can be achieved this way (Copeland and Carter, 2017). Approximately 50% of the total energy consumption of a WWTP can be provided by biogas from anaerobic digestion (Hao *et al*., 2015), with sludge pre-treatments enhancing the biomethane yield further. There is also research on improving the conversion of biogas into electricity by altering fuel cells and optimising thermal conditions (Gandiglio *et al.,* 2017). Microbial fuel cells present potential for direct biological conversion of WWTP organic matter into electricity, however, without significant improvements they cannot compete with anaerobic biological conversion (McCarty *et al*., 2011). Furthermore, re-using the nitrogen and phosphorus from WWTPs for crop fertilisation can offset the considerable energy consumption of producing synthetic fertilisers (Danuta, 2018).

A valuable tool for improving wastewater energy intensity amongst water companies is benchmarking. By utilising key performance indicators, it is possible to find the optimal performers and evaluate companies against similar entities or standardised values (Krampe 2013; Torregrossa *et al.,* 2016). By doing this, companies can identify and prioritise areas for improvement and learn from best practices (Walker *et al.,* 2019; Walker *et al*., 2021). Vaccari *et al*. (2018) evaluated energy consumption within Italian WWTPs and documented that energy benchmarks had not been extensively investigated. They highlighted only the USA (WEF 2009; WERF 2011; Wang *et al*., 2016), Australia (Krampe 2013; de Haas *et al.,* 2015), Japan (Mizuta and Shimada, 2010; Hosomi, 2016), Austria (Lindtner *et al.,* 2008; Haslinger *et al.*, 2016), Germany (Wang *et al*., 2016), Sweden (Lingsten *et al.* 2011), Denmark, Norway and Finland (Gustavsson & Tumlin, 2013) as the areas where energy benchmarks had been previously studied. In addition to these studies though, there has been alternative research into energy consumption of wastewater in various countries. They include Portugal (Vieira *et al*., 2019), Finland (Gurung *et al*., 2018), Mexico (Valek *et al*., 2017), Brazil (SNIS, 2014), India

(Soares *et al*., 2017), Singapore (Hernández-Sancho *et al.*, 2011), South Korea (Chae and Kang, 2013), China, and South Africa (Wang *et al*., 2016).

Most of these studies, although offering value, have limited sample sizes and offer little insight into performance across countries or regions effectively. There are international benchmarking organisations such as the International Benchmarking Network for Water and Sanitation Utilities (IBNET), European Benchmarking Co-operation (EBC), Water Utility Partnership for Capacity Building in Africa (WUP), South East Asian Water Utilities Network (SEAWUN), which collate and provide an expanse of valuable information. However, energy metrics and samples are often limited and dated, particularly for wastewater, reducing the extent of research outputs.

This study undertakes international benchmarking and evaluates the energy intensity of wastewater treatment at company level. The advantage of international benchmarking is that it allows representation and evaluation of performance with the largest sample possible. Furthermore, an international sample enables a view into possible reasons behind performance, which is particularly relevant for assessing the future path of countries attempting to alter their wastewater treatment standards and methods. However, despite the advantages of opening up benchmarking to an international scale, some limitations must be navigated. The expanded sample size and variety can lead to un-equal comparisons, particularly regarding effluent quality standards and the amount of pollution being removed (Berg, 2013).

This study had several objectives. Foremost, to explore the energy intensity of wastewater treatment on an international scale with the most up-to-date data available and an effluent quality control to ensure credible comparison. Secondly, to investigate reasons for varying performance, contexts including regional, legislative, and size differences. Thirdly, to assess the carbon impacts of energy intensity relative to each region. Finally, to evaluate areas for improvement in international benchmarking practices. The international scope of the study helped address many of the knowledge gaps highlighted earlier, and the work can be of use to water industry, benchmarking organisations, energy efficiency analysts, and regulators, by giving recent results of wastewater energy intensity and associated carbon from many countries across the world, along with explicit suggestions on improving future data collection, reporting and analysis.

6.2. Methodology

6.2.1. Data description

The core indicator used was kWh/m^3 of wastewater treated, kWh being gross electricity consumed. Since the level of wastewater treatment impacts on energy consumption (see Section 6.1), a control on water quality was deemed necessary. There were limited possibilities with available data however; wastewater receiving secondary treatment or better at volumes of 95% and above was incorporated. The main source of data was the International Benchmarking Network for Water and Sanitation Utilities (IBNET, 2021) database, this was supplemented by company reports and other national benchmarking schemes, which collectively covered Greece, Italy, Spain, Sweden, Canada, United States, UK, Australia, New Zealand, Denmark and Netherlands. The sample years were 2014-18 however, only one year of data was required within that range for a company to be used in the study to maximise the sample size. It is possible that by using one entry within the five-year range, an abnormal year of heavy rainfall and increased wastewater treatment could be used; however, the indicator kWh/m^3 should negate this. Companies with multiple data points throughout those years had their values averaged. Extra data from the IBNET database was utilised to conduct part of the analysis comparing energy intensity of primary only treatment (>95% of total volume treated) and the core sample data. This extra primary treatment data had 29 companies from nine countries, the comparison with core sample was undertaken with only the same nine countries for the fairest results.

External data to this from journal articles were used in Section 6.3.3 to enable a better understanding of regional differences, covering Portugal, Germany, Finland, Brazil, Mexico, India, South Korea, China, Japan, Singapore, and South Africa. This external data did not have the same treatment quality controls that the core data had and was based largely on samples of WWTPs, not companies, and therefore was not incorporated into the core sample. Summary statistics for the sample are available in Table 6.1, with a full data table and data sources available in the Supplementary Information.

Table 6.1. *Summary data for the core, external and primary treatment samples.*

Sample	Indicator	Countries	Companies	Average	Min	Max	SD
Core sample	kWh/m^3	31	321	0.89	0.04	3.11	0.49
External sample	kWh/m^3	11	N/A*	0.40	0.08	1.15	0.25
Primary treatment only	kWh/m^3	9	29	0.36	0.01	1.25	0.29

*****External sample made up of myriad data including WWTPs and tertiary average data from other studies.

6.2.2. Data Analysis

6.2.2.1. Spearman's rank correlation coefficient

To assess the relationship between a) the size of companies and their energy intensity, and b) the percentage of tertiary treatment received in each country and energy intensity, in Section 6.3.1, Spearman's rank correlation coefficient (r_s) was utilised. This non-parametric approach was chosen due to the sample being non-normally distributed and has the advantage of being relatively insensitive to outliers. r_s is calculated according to the following equation:

$$r_s = 1 - \frac{6\sum d^2}{n(n^2-1)} \qquad (6.1)$$

where d is the difference between ranks for each variable data pair and n is the number of data pairs. When r_s = 1 the data pairs have a perfect positive correlation (d = 0) and when r_s = -1, the pairs have a perfect negative correlation.

6.2.2.2. Kruskal-Wallis test

To test if there was a significant energy intensity difference between the size groups in Section 6.3.1, a Kruskal-Wallis H test was used. This non-parametric approach was chosen, as there was not a particular distribution of the energy intensity data. The H statistic is calculated with:

$$H = \left[\frac{12}{n(n+1)}\sum_{j=1}^{c}\frac{T_j^2}{n_j}\right] - 3(n+1) \qquad (6.2)$$

where n is the sum of sample sizes for all groups, c is the number of groups, T_j is the sum of the ranks in the j^{th} sample, and n_j is the size of the j^{th} sample. To decipher whether the medians of the groups are differing, the H value is compared to the critical chi-square value at an alpha level of 0.05 in this instance (degrees of freedom = 3). If the critical chi-square value is < the H statistic, there is significant difference between the groups, whereas if the chi-square value is $\geq H$, there is not enough evidence to suggest that the medians are unequal.

6.3. Results and Discussion

6.3.1. Size and energy intensity

Typically, the expectation is that larger WWTPs and companies are more efficient due to economies of scale (Molinos-Senante *et al*., 2018b). However, this is not always the case. At certain scales, diseconomies can occur, and within rural environments where treatment plants cover large areas, water conveyance can affect energy and financial efficiency (Saal *et al*., 2013; Walker *et al*., 2020).

The international sample utilised here is displayed in Figure 6.1, with each company and their energy intensity being plotted against their size, measured in population served. The range of data (0.04 to 3.11 kWh/m^3 and 500-15,000,000 in population served) meant that outliers and non-normal distribution could affect inferences from analysis. To negate this, Spearman's rank was utilised, and size categorisation was undertaken to group similar sized companies together, results of which are in Table 6.2 with their associated mean average electricity intensity.

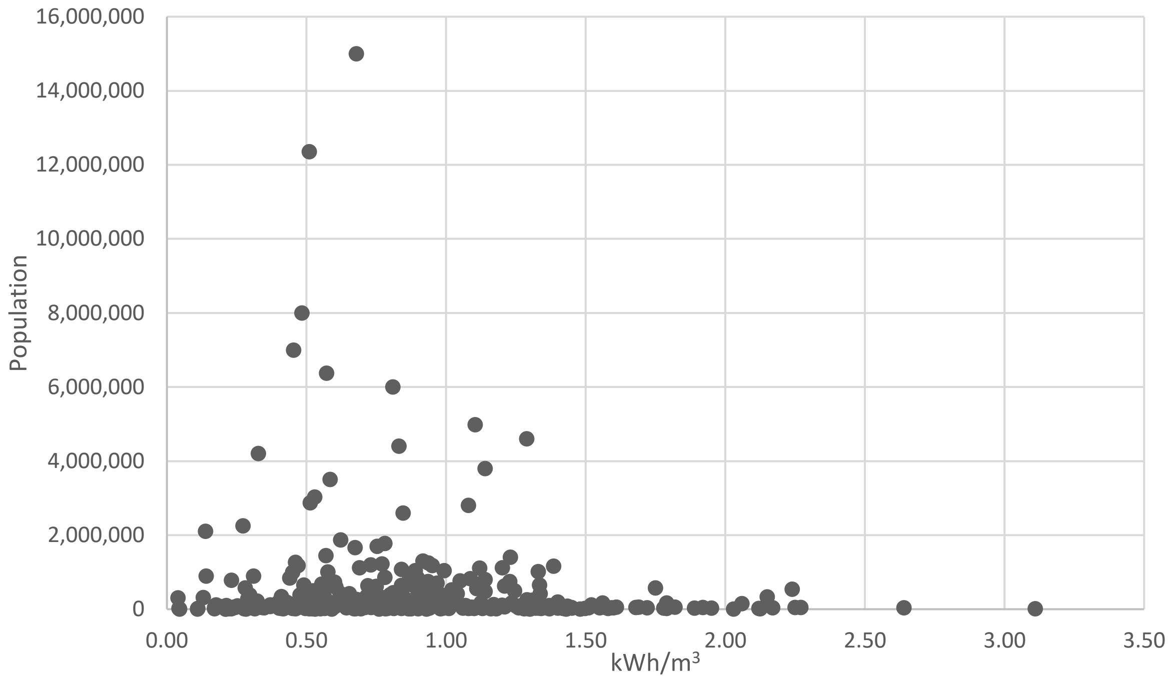

Figure 6.1. *Electrical intensity of 321 companies plotted against their size (measured in population served).*

The whole sample has a r_s value of -0.108, suggesting, as companies get larger, they consume less electricity per cubic metre of wastewater treated; however, it is not a strong relationship and displayed a non-significant p-value. A Kruskal-Wallace test revealed there was a significant difference between the four applicable groups (p-value of 0.015); implying size does influence energy intensity. Furthermore, the group of companies serving over 1,000,000 people had a slightly lower average kWh/m^3 compared to the rest of the sample, with the r_s value showing a weak negative relationship to a significant degree (p-value of 0.024), supporting inferences that larger companies have slightly lower energy intensity. This appears to be a non-lineal relationship since the highest average energy intensity is from the 10,001-100,000 group, which with the 100,001-1,000,000 group show very weak positive relationships, whilst the smallest applicable category of 1001-10,000 shows a very weak negative result. These results indicate that the extreme companies on the size spectrum are not necessarily handicapped in their pursuit for efficiency, and therefore should actively seek to learn from the top performers, regardless of their size.

Table 6.2. *The company size categories based on population served, their average electricity consumption, Spearman's rank correlation coefficient, and associated p-value.*

Size category	n	Average kWh/m^3	Spearman's rank correlation coefficient r_s	P-value
0-1000	1	1.30	N/A	N/A
1001-10,000	21	0.86	-0.07315	0.753
10,001-100,000	141	0.99	0.05516	0.516
100,001-1,000,000	118	0.82	0.01702	0.855
1,000,001+	40	0.78	-0.35685	0.024
All	321	0.89	-0.10778	0.054

It is possible that economies of scale for wastewater treatment companies are only present at the very large size (>1,000,000) as Table 6.2 hints towards, which could be the case in reality; alternatively, there may be other influencing factors not captured within the available data. For example, the economies of scale relationship could be strong between WWTPs, which is impaired when evaluating the overview of companies and here we only have size of companies that does not necessarily represent the size of their treatment plants. Another factor often heavily linked with energy intensity is the level of treatment the wastewater receives (as discussed in Section 6.1), which is at least partially dependent on regulatory standards that differ from region to region. The data used ensured that at least 95% of the wastewater from each company received at least secondary treatment. This was an important effluent quality control as data collected, available in the Supplementary Information, showed companies that treated ≥95% wastewater to only a primary level only consumed 0.36 kWh/m^3 compared to 0.76 kWh/m^3 for companies that treated ≥95% wastewater to at least a secondary level in the same countries. Even within secondary wastewater treatment though, there can be variances with the technologies utilised and therefore differing levels of energy consumption; for example, aeration can be conducted with turbines, diffusers and in some cases, not at all (Guerrini *et al.*, 2017). Having a quality control in the data was important however, without more granular data on how much of that wastewater was treated to a tertiary extent; relationships within the results could be misrepresented. As Figure 6.2 shows, secondary treatment or better actually represents mostly tertiary treatment in many EU member states. Spearman's rank correlation coefficient was conducted with the tertiary treatment percentage data from Figure 6.2 and the matching countries in the energy intensity sample collected. The relationship was positive but non-significant for all valid data (r_s 0.36, p-value 0.2) and when using countries in the energy data sample that had over 15% of population (r_s 0.49, p-value 0.33). Although the results showed tertiary treatment did not cause significant increases in energy consumption, more tertiary treatment will clearly increase energy consumption as the technologies in Section 6.1 showed. This increase, even if not statistically significant, can obscure results when data is only available as secondary treatment or better.

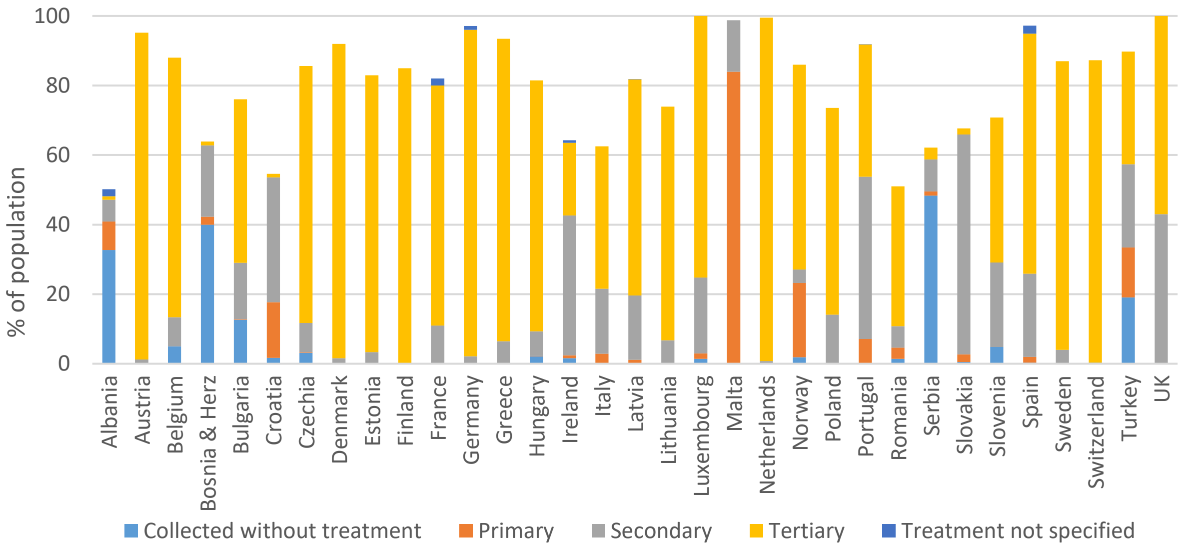

Figure 6.2. *The proportion of urban wastewater collected and the level of treatment applied as a percentage of the population in 2017 for EU states (European Environment Agency, 2020).*

6.3.2. Regional differences

To assess regional variances and further investigate the effect of wastewater effluent quality standards on energy consumption, grouping of companies was completed based on their legislation and United Nations (2021b) Sustainable Development Goal regional groupings. A selection of countries and their summarised wastewater parameters is presented in Table 6.3, however; a more detailed version is available in the Supplementary Information. The EU Urban Wastewater Treatment Directive regulates the level of treatment by implementing required removal efficiencies for pollutants within the wastewater that is discharged into water bodies to protect aquatic ecosystems. Non-EU states are often characterised by differing approaches to establishing the legal regulations regarding wastewater discharge into surface waters (Preisner *et al*., 2020). In countries that were formerly part of the Soviet Union, a materially different method is in place, which is based on the assumption that the level of wastewater treatment must ensure the normative water quality in the control cross-sections of individual water bodies (Neverova-Dziopak, 2018). This means the maximum allowable load discharged from each WWTP is defined based on the category of the receiving water, its specific characteristics, and the construction of the wastewater outlet. These different approaches exemplify the difficulty in directly comparing regions, however, the major effluent maximum standards give a reasonable guide, albeit whilst mindful of distinct contexts.

Table 6.3. *Summarised wastewater effluent standards for a selection of the total sample, a fuller version is within the Supplementary Information.*

Region	**WWTP category**	**COD (mg/l)**	**BOD_5 (mg/l)**	**Total N (mg/l)**	**Total P (mg/l)**	**TSS (mg/l)**
EU	<2000 PE	125	25	n/n[a]	n/n	35
	2000-10,000 PE	125	25	n/n	n/n	35
	10,000-100,000 PE	125	25	15	2	35
	>100,000 PE	125	25	10	1	35
HELCOM	300-2000 PE	n/n	25	35	2	35
	2000-10,000 PE	125	15	30	1	35
	10,000-100,000	125	15	15	0.5	35
	>100,000 PE	125	15	10	0.5	35
Denmark	General	75	10	8	0.4	20
Moldova	General	125	25	15	2	35
Australia (Tasmania)	Fresh	n/n	15	15	3	n/n
	Marine	n/n	20	15	5	n/n
Australia (Queensland)	Surface	n/n	30	15	6	45
Nigeria	Varied	60-90	30-50	10	2	25
India	General	250	30	10	5	50-100
Fiji	General	n/n	40	25	5	60

[a]n/n not normalized parameter

Table 6.4 shows that the EU companies had the largest average energy intensity at 1.18 kWh/m^3, whilst all other regions averaged much lower, ranging between 0.58-0.64 kWh/m^3, apart from Russia and the former states of the Soviet Union who averaged 0.82 kWh/m^3. The

EU UWWTD directive is widely appreciated to have some of the strictest effluent standards in the world (Morris *et al*., 2017), so it was anticipated for those countries to have a higher energy intensity due to higher levels of treatment requiring more energy (Capodaglio and Olsson, 2020). Despite this, it is still a little surprising that it is so high compared to others, considering many EU countries utilise some of the most efficient treatment techniques and technologies (United Nations, 2017; Preisner *et al*., 2020), such as those discussed in Section 6.1. It is expected then, that as regions with lower effluent standards improve to similar levels of advanced economies, their energy consumption will increase too.

Table 6.4. *Regional data description displaying average energy consumption.*

	EU UWWTD	**Transition to UWWTD**	**Russia & former Soviet Union states**	**Developed Oceania**	**Developing Oceania**	**Central & South America**	**North America**	**Sub-Saharan Africa**
No. Countries	12	3	5	2	5	1	2	1
No. Companies	112	31	126	43	5	1	2	1
Average kWh/m^3	1.18	0.62	0.82	0.65	0.64	0.64	0.57	0.58
S.D	0.43	0.58	0.41	0.42	0.40	N/A	0.05	N/A

In addition to compliance with relevant wastewater effluent legislation, there are alternative possibilities for the variance between the regions. For example, some countries may require different technologies relative to their environmental circumstances, such as areas with water demand higher than consistent supply. An effective solution is to re-use wastewater for non-potable requirements, as is the case in many countries throughout the globe including China who had the most wastewater reuse by volume (14.8 million m^3/day), and Qatar which has the most reuse per capita (170,323 m^3/day per million capita) (Jimenez and Asano, 2008). Though necessary, the processes for reusing wastewater are often energy intense compared to typical wastewater treatment. Ozonation, a common wastewater reuse treatment, consumes approximately 0.27 kWh/m^3 *(*Meneses *et al.,* 2010*),* however, often a collection of treatment technologies is utilised and can add significant energy consumption on top of the baseline, exemplified by San Diego and Los Angeles utilities who consumed an extra 0.93 kWh/m^3 and 0.49 kWh/m^3, respectively (National Research Council, 2012). This can be even more substantial as water scarcity increases, for example, in Australia, energy use for enhanced effluent is projected to grow between 130% and 200% by 2030 (Capodaglio and Olsson, 2020).

Data that are more detailed would clearly enable higher quality inferences from the analysis, which is epitomised in what having influent and effluent quality could facilitate. It would permit accurate pollutant removal efficiencies to be assessed; currently without this data, some regions are perhaps being misrepresented. For example, it is probable that countries adhering to the EU UWWTD are removing more pollutants on average than those countries transitioning to the Directive (Sanfey and Milatovic, 2018), which would at least partially explain the energy consumption deficit (0.56). The lack of influent and effluent data can be paramount if the sampling has captured areas within a region that treat significant volumes of industrial wastewater. The removal of metals from industrial wastewater can be energy intensive with techniques such as chemical precipitation, ion exchange, and electrochemical removal, although there are less utilised technologies with lower energy consumption like polymer-supported ultrafiltration and complexation–filtration as Barakat (2011) discusses in detail. Guerrini *et al*. (2017) showed in their study of 127 Tuscan WWTPs that a 1% increase of inflows from industry will decrease energy efficiency by 28%. If the sample has areas that treat high volumes of industrial effluent, then they would have performed poorly in this analysis.

The regional and global perspective could look very different depending on the data available. For example, the average energy intensity for the whole sample in this study was 0.89 kWh/m^3, within the wide range of global average estimates reported by Wakeel *et al*. (2016) of 0.38-1.12 kWh/m^3 based on different studies. The disparity between these results is likely due to differences in the context of various data. Some may be temporally divergent or have representativeness issues where a few WWTPs may represent a company, a few companies may represent a country, and a few countries may represent a whole region. Table 6.4 for example, shows how Central and South America, North America, and Sub-Saharan Africa have very few countries within them and those countries only have one company representing them, although this is possible when a quality control (≥ secondary treatment for ≥ 95% of volume) reduces sample size. Having representativeness issues is not ideal; however, the practice is carried out by international benchmarking organisations such as the EU Benchmarking Co-operation (2020), when more data is unavailable. In addition, there may be biases in reporting where companies who may already be performing well or actively trying to improve are more likely to actively share their wastewater energy data, whereas poorer performers may not disclose the data or just not have the means to collect it thus, undermining benchmarking efforts. Although there are potential issues around the sampling parameters, data representativeness, and potential reporting biases, the results presented here are the best current indication of reality, which is discussed further in Section 6.3.5.

6.3.3. Country-level analysis

To further evaluate possible influences of energy intensity and the practicality of the data, the scope was narrowed to country-level analysis. The global coverage of the dataset was patchy despite extensive efforts to collect wide-ranging data, therefore some partially mismatching data in terms of company-level and known WWTP-level data was used from other studies to further inspect differences in electrical intensity between countries (Figure 6.3).

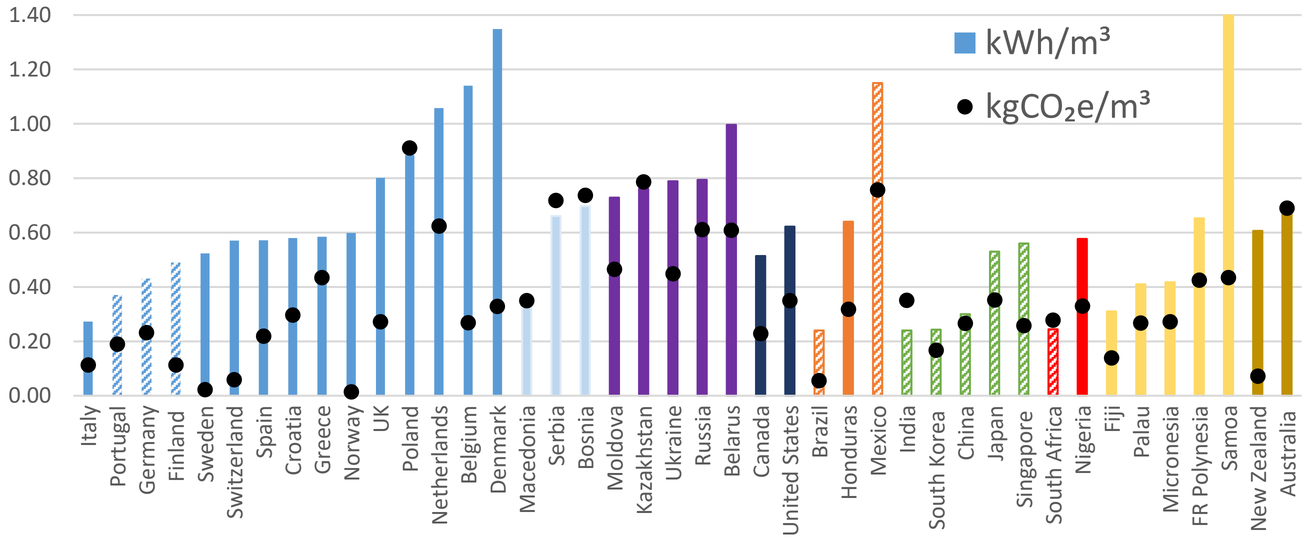

Figure 6.3. *Energy intensity (kWh/m^3) and associated greenhouse gas emissions ($kgCO_2e/m^3$) for all countries in the core sample, supplemented by external WWTP data, represented by striped columns (42 countries in total). The colours represent regional separation.*

The lowest energy intensity was observed in Brazil (0.24 kWh/m^3), India (0.24 kWh/m^3), South Korea (0.24 kWh/m^3), South Africa (0.24 kWh/m^3), and China (0.3 kWh/m^3). All five of these countries were from the external data, which were collated through individual studies on WWTPs; therefore, it is probable the countries are not being fully expressed due to limited sample size, as discussed in the previous section. There is also the major influencing factor of the disparity of wastewater effluent quality within the sample as examined above; especially considering the external data could not be filtered by secondary treatment or better as the main sample was. These five countries with the lowest energy intensities have some of the lowest wastewater quality requirements in the sample as Table 6.3, the Supplementary Information, Choi *et al*. (2015), Edokpayi *et al*. (2017), Never and Stepping (2018), and Wang and Gong (2018) document. This means these countries are more likely to perform the best out of the 42 countries because they are using less energy intensive, but less effective, processes. It should be noted though that these countries have large disparities of wastewater services, treatment and compliance, and some cities within these countries have established wastewater infrastructure capable of high levels of treatment.

The counties with the highest specific energy requirements for wastewater treatment were Samoa 1.4 (kWh/m^3), Denmark 1.35 (kWh/m^3), Mexico 1.15 (kWh/m^3), Belgium 1.14 (kWh/m^3), and Netherlands 1.06 (kWh/m^3). These countries contrast to the lower energy consuming performers as this group has mixed wastewater legislation and standards, as opposed to having standards from one end of the spectrum. The three European countries show that it is not only higher levels of wastewater treatment with stricter legislation causing perceived inefficiency, it highlights another issue with the data, which is that it is based on gross, as opposed to net, consumption. This issue is exemplified by Denmark who not only have among the most stringent legal regulations regarding wastewater discharges in the EU after reducing their allowable pollution more than the UWWTD (Valero *et al.*, 2018), but heavily utilise energy recovery technologies in WWTPs (Grando *et al*., 2017). The Danish water benchmarking 2019 report (DANVA, 2019) showed six companies actively producing energy via their wastewater treatment at various rates; however, their gross consumption classifies them as energy sinks. The most extreme instance was Kalundbord who had 4.27 kWh/m^3 gross energy consumption but produced 7.9 kWh/m^3 in net energy. By only using gross energy data instead of net, it fails to capture the energy produces by wastewater, which can be substantial. The pure energy intensity of operations is still captured however, under a wider sustainability view; the data does not function adequately.

The energy intensity variations within regions and between countries came as a slight surprise, for countries using the UWWTD and within the developing Oceania, they ranged between 0.27-1.35 kWh/m^3 (SD 0.29) and 0.61-1.40 kWh/m^3 (SD 0.40), respectively. A possible explanation is that whilst countries may share effluent standards, they have differing compliance rates. This is supported by the 10th report on the implementation of the UWWTD (European Commission, 2020), which shows that 95% of wastewater in the EU is collected and 88% is biologically treated. The wastewater quality control indicators in this study only covers the degree of treatment as a percentage, not specific compliance. Furthermore, the same legislation can be managed differently in different countries. For example, Preisner *et al*. (2020) comments that fifteen EU member states including Belgium, Denmark, Netherlands, Poland, Sweden, Finland have identified all their surface water bodies in their territory as sensitive areas, whereas thirteen countries containing Croatia, Germany, Italy, Spain, Portugal, and United Kingdom considered only selected water areas as sensitive (Zaragüeta and Acebes, 2017). The varied identification of water bodies as sensitive and non-sensitive impacts the level at which wastewater needs to be treated and therefore, affects the energy required to treat it.

The importance of energy efficient wastewater treatment is even greater when considering the carbon intensity of fuel mixes powering electricity grids. As Wang *et al*. (2016) commented, there is a general lack of understanding regarding electricity consumption and carbon emissions between countries on the international scale. To evaluate GHG emissions from wastewater energy consumption, country conversion factors from the EcoInvent v3.7

database (method: CML 2001 superseded, GWP 100a) were used and multiplied with the electricity intensity indicator (kWh/m^3 * $kgCO_2e/kWh$ = $kgCO_2e/m^3$). Figure 6.3 displays the $kgCO_2e/m^3$ for all 42 countries in the extended sample, showing Poland, Macedonia, Serbia, Bosnia, Kazakhstan, India, South Africa, and Australia all produce more than one kg of CO_2e/kWh, meaning their GHG contribution is particularly substantial relative to the kWh/m^3 figures. This becomes particularly problematic in countries with already high-energy intensity for treating wastewater, as is the case with Poland who consume 0.89 kWh/m^3 and have the highest carbon footprint intensity with 0.91 $kgCO_2e/m^3$. Conversely, a clean electricity grid can affectively mitigate wastewater treatment inefficiencies, exemplified by Norway who emit just 0.013 $kgCO_2e$ per cubic meter, despite consuming 0.60 kWh/m^3, followed by Sweden and New Zealand, emitting 0.02 and 0.07 $kgCO_2e/m^3$ whilst consuming 0.52 and 0.61 kWh/m^3, respectively. Sustainability in the context of GHG emissions from wastewater treatment then, depends on influent and effluent water quality, treatment technologies, effluent quality standards and compliance with those standards, and electricity fuel mix.

6.3.4. Learning from limitations

Results presented in this study offer the best view of the state of international wastewater energy intensity with current available data; however, as the sections above have discussed, there are avenues to improving future analysis. Foremost, there is a need for more data; this sample included 31 countries and 321 companies in the core sample, before expanding it to 42 countries with more sporadic WWTP data from individual studies. Chini and Stillwell (2017) also call for more availability and transparency in water utility data in their study of the United States water sector, highlighting that the only means of acquiring data is through open record requests of individual utilities. Even following data requests from over 200 utilities, only 61% responded. Sato *et al*. (2013) further emphasise the need for global, regional and country level data, illustrating that only 55 countries have data available on wastewater production, treatment and reuse, with 57 countries having no information available at all. Whilst the study is somewhat dated now, clearly these themes are still valid. A lack of data not only makes it difficult to affectively evaluate energy intensity and conduct benchmarking, it also causes problems of representativeness. With only limited companies reporting their data, it can lead to biases within the sample. For example, perhaps only the best performers who already partake in benchmarking and external analyses make their data publicly available (Denrell, 2005). In combination with general limited coverage within areas, a lack of representation causes analyses to miss the full picture, therefore reducing the quality of recommendations and real-world improvements.

The need for more detailed and granular data alongside additional data is paramount for enhanced assessments of wastewater treatment in the future. A subject at the core of the results in this study is the difference between net and gross energy consumption in reporting. Net energy consumption would enable more meaningful sustainability outcomes as energy production and strain on the electricity grid are encompassed, which are integral elements for modern WWTPs. Additionally, compliance rates with wastewater effluent standards would enhance the accuracy of analysis, as currently regions with similar standards are grouped together, although in reality their compliance rates may differ greatly. These extra and more detailed data would also enable the inclusion of explanatory factor analysis to improve understanding of how exogenous influences can be managed to enhance efficiency. Currently, the data conditions of scarcity and factors already influencing results as the ones mentioned above would mean explanatory factor analysis would not offer value. Finally, this study used wastewater treated at least to secondary treatment level or better, but more detail on which level of treatment has been used and what volume that was applied to would enable a better understanding of the current state of wastewater treatment in many regions. For the best understanding of treatment levels, having key pollutant removal data or influent vs effluent data would be required. An alternative unified metric to kWh/m^3 that incorporates energy and a quality aspect would be best for optimum intensity benchmarking. An example is energy per unit of organic load removed ($kWh/COD_{removed}$), which is a simple performance indicator that conveys meaningful information. This has been used in other studies (Patziger, 2017) and offers real value however, it is not uniformly applied. Christoforidou *et al.* (2020) exemplified how useful this metric can be in their energy benchmarking of WWTPs in Greece, particularly in combination with other energy key performance indicators that cover volume treated (kWh/m^3) and population equivalent (kWh/PE). An increasing number of studies are implementing and recommending a quality parameter to be included in WWTP analysis as Clos *et al*. (2020) notes. This is a positive development however, the highest levels of treatment where pathogens are being removed using energy intensive methods, e.g., disinfection via UV, chlorination, and ozone treatment (Chuang *et al*., 2019), are still not captured in these indicators. Using multiple quality indicators or the development of a framework covering all key technologies and pollutants may be the best solution for future analyses. Although there is more demand for quality indicators to be ubiquitous in measuring and reporting, and there are differing approaches in including quality within energy efficiency assessments, it is important that utilities, regulators, and academics unify their metrics, to ease comparisons, analysis, and ultimately, facilitate learning and improvement.

6.4. Conclusions

The objectives of this study were to investigate the international energy intensity of wastewater treatment, explore variances in performance, evaluate the carbon impact of the energy consumption, and assess how to improve international benchmarking practices. The global average electricity consumption for wastewater treatment was 0.89 kWh/m^3. Larger companies serving over 1 million customers display slightly lower specific consumption, of 0.78 kWh/m^3. When viewing regional groupings, EU companies had the highest average energy intensity at 1.18 kWh/m^3, with three EU countries standing out: the Netherlands (1.06 kWh/m^3), Belgium (1.14 kWh/m^3), and Denmark (1.35 kWh/m^3). Countries with the lowest energy intensity varied from Brazil, though India and South Korea to South Africa (averaging 0.24 kWh/m^3). This appeared to be a symptom of the energy data being gross consumption and there being a disparity between wastewater quality standards, since energy production at WWTPs was not captured and the lowest energy consumers had some of the worst standards, and vice versa. The influence of energy consumption on GHG emissions was diverse owing to interaction with widely differing emissions intensities of grid electricity; Poland had the highest carbon footprint with 0.91 $kgCO_2e/m^3$, whilst Norway emitted just 0.013 $kgCO_2e$ per cubic meter of, despite consuming 0.60 kWh/m^3, showing the importance of energy intensity on particular infrastructures. Although this study provided some valuable quantifiable results, the conclusions stemming from the limitations of carrying out the benchmarking exercise are just as crucial. There is a lack of quantity, quality and granularity in existing global wastewater data, making it difficult to fully analyse the impact and potential paths to improve of wastewater treatment. A lack of data generally leads to a lack of representativeness of certain regions, skewing comparisons with limited sample sizes. The two changes that would have the most significant impact for future analyses are to have influent vs. effluent quality and net energy consumption data, which would increase the accuracy of studies, circumnavigating varying legislative effluent standards and compliance rates. The large international sample size, energy data with a quality control, GHG analysis, and specific benchmarking recommendations provide novel results which could be of use to water industry operators, benchmarking organisations, energy efficiency analysts, and regulators.

7. Collective discussion

This thesis covers two major aspects of scientific research, 1) pushing the boundaries of existing knowledge 2) re-testing some aspects of existing research with similar methods and indicators to validate and add weight to existing knowledge. The nature of modern academia means that people are judged on number of citations and their publications in journals with higher impact factors, which is a fair metric when others do not exist. However, this means academics are driven to produce on-trend and thematic research, sometimes leaving a limited number of publications to represent the authority and acceptance on knowledge in certain fields (Fong and White, 2017; Oliver and Cairney, 2019). Fortunately, in the performance analysis niche of which this thesis sits, there was opportunity to address both aforementioned aspects of scientific research simultaneously throughout the thesis, with a focus on delivering multitudinous value.

The research papers synthesised here have individually and collectively contributed to academic literature and provided outputs that can assist the water sector, regulators and analysts. An integral element of performance analysis and benchmarking is that it is a continuous process, which enables practitioners to recognise changes in efficiency and performance relative to others (Ettorchi-Tardy *et al.,* 2012). Foremost, this is what the research offers through years of data collection and analysis – an up-to-date set of varied results, that can inform decision-making now and in the future. For example, Chapter 6 collected and examined wastewater electricity consumption data for 350 companies from 42 countries, delivering an up-to-date account of the global status and a useful resource for future analysts and studies. Furthermore, Chapter 5 found that the UK water sector improved in productivity by 1.8% between 2014-18 when evaluating social, environmental and economic factors however, Chapter 3 discovered economic and environmental inputs could reduce by 19.4% and 15.8%, respectively, and still deliver the same level of water supply and treatment. Potential reductions were perceived to be significantly higher in Chapter 4, although this was symptomatic of having a large spread in efficiency estimates using the DEA method, where some companies were perceived to be significantly less efficient than others. Chapters 3, 4, and 5 show that despite the improvements made in the UK water sector, there are still areas for improvement and these studies offer a starting point to investigate them. This was particularly evident in Chapter 5, where a breakdown of technical and efficiency change occurred using the HMPI, indicating that the majority of UK WaSCs had economies of scale and scope with productivity largely being driven by improved operational practices of existing infrastructure and resources.

An especially interesting finding was that the water companies throughout the data chapters had mixed performance ranges. In Chapters 3 and 5, they were relatively homogenous in their performance, but in Chapters 5 and 6 there was a significant efficiency range, meaning there were some companies severely lagging behind others. The results differed between chapters due to the differing methodologies, indicator choices, and samples. However, each chapter did highlight that the sharing of best practice and informed investment would be beneficial to the water sector. In theory, sharing of best practice should be one of the rare positives of the unique monopolised environment that the water industry operates in, since a water company being more efficient should not significantly negatively affect other companies since customers cannot switch and those companies are not competing against each other.

Water companies are always driving (and being driven) to improve efficiency, demonstrated by the UK industry-wide targets of reducing leakage by 16% by 2025 and a further reduction to half of the current levels by 2050 (Water UK, 2020), and the commitment to achieve net zero operational GHG emissions by 2030 (Water UK, 2021). The latest data (2019/20) signifies that these targets are slowly becoming a reality as there have been active efficiency improvements in many areas within the past year, with leakage being reduced by 7%, average supply interruptions down one minute to 12 minutes, and consumption per capita down one litre per person per day to 142 litres (DiscoverWater, 2021). To understand progress towards targets, and past them towards full optimisation, alternative more complex methodologies can offer part of the solution, where company efficiency can be investigated in-depth by including many different important indicators together (Singh *et al*., 2009; Vilanova *et al*., 2015). This is where performance analysis and benchmarking academics have played a significant role, and where the research in this thesis can contribute.

The methodologies used in Chapters 3, 4, and 5 have had limited application to the water sector in academia, as noted in the corresponding chapters, and even fewer applications in industry (Maziotis *et al*., 2021). Chapter 5 used the HMPI methodology to evaluate efficiency over six years, which has benefits of being able to compute multiple inputs and outputs and decompose results into technical and efficiency change, that can indicate whether performance is being driven by capital investment or operations management. Furthermore, it has advantages over other similar complex multi-input and output efficiency frameworks in that it satisfies all other index conditions, including multiplicative completeness and transitivity tests (O'Donnell, 2012), functions within a simultaneous input and output orientation, and can be computed under both CRS and VRS. Chapter 5 was able to demonstrate the positives of the HMPI for potential use in the water sector, similar to Chapters 3 and 4, which utilised a double-bootstrapped DEA approach. This approach attempted to correct some of the statistical biases that can occur when using DEA but kept the positives of the method such as providing a multi-criteria analysis, being able to generate weightings of the inputs and outputs endogenously, and not requiring a priori assumptions regarding the functional relationship between variables. These chapters showed that the standard DEA model is somewhat flawed, possibly explaining why, following application in their 1994 price review, OFWAT no longer rely on it (Nourali *et al*., 2014). In addition, Chapters 3 and 4 also presented a good variant of DEA in the double-bootstrap method that can contribute to academia and the water sector, with a notable positive of allowing analyses to investigate the effect of explanatory variables too.

Exploring explanatory factors is vital to understand reasons behind performance results. This can allow more informed and accurate regulation, and when the factors are at least partially within the control on the company, enable targeted efficiency improvements. Chapters 3, 4, and 6 all covered explanatory factors in some capacity. Chapters 3 and 4 for example, analysed the effect of *leakage*, *consumption per capita*, *population density*, rurality, *surface water abstraction percentage*, *number of abstraction sources*, *average pumping head height*, and the *proportion of water passing through the largest 50% of treatment works* on economic and environmental performance. Whereas Chapter 6 analysed the role of size, region, and wastewater effluent quality in the context of treatment energy intensity. A selection of these factors were relatively novel to academic analyses similar to those conducted here, including *number of abstraction sources*, *average pumping head height*, the *proportion of water passing through the largest 50% of treatment works*, and the rurality framework. The results from these variables provided new knowledge in how they may specifically affect performance. The other variables are widely viewed as likely influential and therefore have been frequently included in previous studies on the water sector (Vilanova *et al*., 2015; Alegre *et al*., 2017). The benefit to still including them in the studies within this thesis and future studies is that they provide validation, or challenge, previous studies and existing analyses, and can validate applied methods which are somewhat novel to this area of academia. Collectively then, the reviewed explanatory factors enable water companies to change certain aspects to improve efficiency with factors that they at least partially control (e.g. *leakage*, *proportion of water passing through the largest 50% of treatment works*), have more confidence in potential new analytical methodologies, and can inform regulators to more fairly adjust targets and administer controls by understanding performance in the context of variables not directly affected by water company management (e.g. rurality, *surface water abstraction percentage*).

The thesis has filled various research gaps in the literature and supplemented external research with validation of numerous methodologies and approaches. However, some of the most valuable outputs may be through accentuating important topics pertinent for future research and water management. For example, the uniqueness of the water sector is not a perfect fit for many econometric and efficiency analyses. Water companies, unlike many conventional companies, do not want to maximise their service or product outputs (i.e., water supplied and wastewater treated), since controlling peak flow, managing water resources, and conducting sustainable abstraction are highly valued alongside volume sales (Arfanuzzaman and Rahman, 2017). Measuring efficiency based on the lowest financial or energetic inputs for the most service outputs is therefore problematic, especially when companies pay towards reducing water produced via leakage fixes and education schemes to reduce consumption (Horne, 2020), as this skews the typical efficiency outlook. This was a theme mostly highlighted within Chapter 5 but was a culmination from Chapters 3 and 4. An alternative to the typical input-output approach was to change the indicators in the assessment, which opened the opportunity for more social and environmental indicators as Chapter 5 showed. The difficulty with changing the indicators is finding suitable substitutes that still represent the core company services and operations, which is why the application of efficiency in terms of minimal input to maximum output for water companies is still a decent representation of performance, but clearly the flaws require future research to either acknowledge the problem or conduct alternative analyses.

Efficiency measured as minimising inputs and maximising outputs is a fair and accurate way to represent performance most of the time. However, in addition to the problem outlined above, there is more of a fundamental issue with viewing performance in this way, especially when utilising economic inputs, as most studies do (Berg and Marques, 2011; Worthington, 2014; Goh and See, 2021). By companies being rewarded either through high rankings, compensation or minimised fines, when they are essentially chasing the bottom line of spending for maximised outputs, it can lead to an increasingly antiquated network or poorly paid staff, which can perpetuate social inequality or isolate companies from the best available employees that may hold the key to innovative practices for their company and the wider water utility community. This highlights the requirement for good management, an array of affective regulation, and extra appropriate variables within efficiency analyses. The thesis addresses this potential issue by incorporating an evaluation of the best indicator choices throughout all results chapters. Chapter 3 uses operational CO_2e and the proxy of *length of mains and* *sewage pipes* to represent embedded CO_2e as environmental inputs, alongside *OPEX* and *CAPEX*. Chapter 4 tests common proxies and has energy as an input with *OPEX* and *CAPEX*, then Chapter 5 uses eight different indicator configurations to compute a productivity model in attempt to find the best combination and show how using alternatives can affect results. Finally, Chapter 6 has the quality of wastewater effluent at the core of the study, ensuring that quality alongside energy consumption is advocated. Following that, there is a discussion around the best means for enhanced future studies with better indicator use, for example, using influent vs. effluent data to fully understand pollutant removal and using net instead of gross energy consumption in some instances to understand the impact of wastewater treatment holistically. Although advancements were made in these chapters, there is still more to be done in academia to try and optimise KPI choice with often limited data.

The results chapters throughout the thesis are all connected through their common goals of measuring and evaluating performance with aspirations to improve that process. The differing aspects of the chapters that have offered diverse value are contrasting sample years and size, KPI usage, type of water company, and methodologies. Although each chapter's value and outputs were unique, they did have similar overall lessons. Insights such as the benchmarking and performance analyses benefitting from more data, data transparency and granularity, and collaboration between academia and the water industry were recurrent throughout and are not necessarily totally unique (Abbott and Cohen, 2009; Carvalho *et al*., 2012; Sato *et al*., 2013; Chini and Stillwell, 2017; Cetrulo *et al*., 2019) but are important nonetheless and are in parts, more specific and informed within this thesis.

8. Conclusions

The goals of this thesis were to analyse the efficiency of UK water and sewage companies, efficiency of wastewater companies internationally, effect of explanatory factors, best methods for multi-input and output analyses, and to review the most appropriate indicators to be used in benchmarking. The research has achieved these objectives and has produced some stark conclusions. Results show that the UK water sector improved in productivity by 1.8% in total between 2014-18 when evaluating the best indicators to represent sustainability and real-world processes that occur at water companies. However, a different study discovered economic and environmental inputs could be reduced by 19.4% and 15.8%, respectively, whilst still delivering the same level of water supply and treatment. Wider research examining wastewater electricity consumption for 350 companies from 42 countries suggested there was vast room for improvement in particular regions too. Global average electricity consumption for wastewater treatment was 0.89 kWh/m^3 however, EU companies had the highest average energy intensity at 1.18 kWh/m^3. This appeared to be a symptom of the energy data being gross consumption and there being a disparity between wastewater quality standards since energy production at wastewater treatment plants was not captured and the lowest energy consumers had some of the worst standards and vice versa. In terms of the role of explanatory factors, many variables were evaluated and of note were *population density* and rurality, which proposed economic and environmental efficiency increases in denser areas due to fewer treatment plants being required. Moreover, the *proportion of water passing through the largest 50% of treatment works* exhibited a significant negative effect on economic efficiency and *average pumping head height*, which displayed a significant negative effect for energy efficiency. Finally, the thesis identified that data envelopment analysis, one of the most popular methods in the benchmarking academic literature, has limitations. However, adaptations, such as the double-bootstrap data envelopment analysis, show promise to overcome the negatives, whilst the Hicks-Moorsteen productivity index navigated restraints of similar methods such as order-m and Malmquist productivity index.

By fulfilling the objectives of the thesis, it is possible to deliver recommendations for future research. It is evident that as more data driven goals are being sought by companies, methodologies need to support that. A few econometric methods were utilised in the thesis however, more testing with various methodologies and iterations of existing approaches would be advantageous to enable the most reliable results. In addition to expanding methodological possibilities, a focus on data is integral for future research and benchmarking to deliver the most affect results. Specifically, an increase in the quantity, granularity and transparency of data would advance studies and ultimately decision-making. The collection of studies presented in this thesis highlight the need for better data, for example influent and effluent data at varying scopes within water companies could form the base of many studies to build from as this would give optimum accuracy of the core operations. As more data becomes available, a focus on implementing more indicators in efficiency studies is also imperative to fully represent sustainability and ensure the uniqueness of water companies is accounted for where higher levels of outputs (i.e., water supplied and wastewater treated) is not necessarily a positive.

The knowledge gaps addressed, and novelty displayed throughout the thesis can have implications for performance and benchmarking analysts, water managers, and regulators. This could be through learning from the use of rarely applied econometric methods to the water sector, and unique indicator applications both in the core model approaches and explanatory factors. Lastly, there is value in the wide-spread data collection and analysis that delivered an up-to-date account of UK water sector and international wastewater efficiency. Collectively, the work can inform decisions made within the water sector and gives a platform for analysts and academics to build upon both now and in the future.

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Appendix 1: Supplementary Information to Chapter 3

1a. Full DEA efficiency tables

Economic

Economic analysis							
DMU	**Non-bias corrected efficiency**	**Original rankings**	**Bias-corrected efficiency**	**Bias-corrected ranking**	**Bias**	**Lower bound**	**Upper bound**
8	1	1	1.012	1	-0.012	0.989	1.023
9	1	2	1.04	2	-0.04	1.002	1.077
1	1.002	8	1.041	3	-0.04	0.99	1.08
11	1	3	1.062	4	-0.062	0.97	1.12
5	1	4	1.096	5	-0.096	0.996	1.181
4	1.074	9	1.099	6	-0.025	1.041	1.122
6	1.098	10	1.191	7	-0.094	1.101	1.277
7	1	5	1.276	8	-0.276	1.21	1.369
13	1.232	11	1.281	9	-0.049	1.22	1.325
10	1	6	1.307	10	-0.307	1.26	1.357
12	1	7	1.315	11	-0.315	1.27	1.393
3	1.361	12	1.431	12	-0.07	1.362	1.49
2	2.048	13	2.175	13	-0.127	2.067	2.237
Average	1.14		1.256		-0.116	1.19	1.312
SD	0.295		0.306		0.109	0.295	0.314

Environmental analysis							
DMU	**Non-bias corrected efficiency**	**Original rankings**	**Bias-corrected efficiency**	**Bias-corrected ranking**	**Bias**	**Lower bound**	**Upper bound**

7	1	1	1.026	1	-0.026	0.96	1.05
8	1	2	1.04	2	-0.04	0.964	1.08
3	1	3	1.079	3	-0.079	0.981	1.155
1	1.034	6	1.082	4	-0.048	1.025	1.125
4	1.105	7	1.14	5	-0.036	1.072	1.173
10	1.119	8	1.158	6	-0.039	1.115	1.187
6	1	4	1.321	7	-0.321	1.243	1.419
9	1	5	1.332	8	-0.332	1.269	1.396
5	1.2	9	1.416	9	-0.216	1.346	1.499
12	1.505	11	1.594	10	-0.089	1.498	1.672
2	1.596	12	1.681	11	-0.085	1.609	1.75
11	1.366	10	1.765	12	-0.399	1.669	1.879
Average	1.096		1.219		-0.122	1.147	1.275
SD	0.159		0.189		0.121	0.184	0.207

1b. All regression results

Indicator	**Unit**	**R2**	**Slope**	**Intercept**
Number of sewage treatment works	number/M property served S	0.823	24.008	-1508.89
Total load treated by STWs in size bands 1-3	kg BOD5/day/M properties	0.792	-5.139	533.304
Total company spend	£/property connected for S&W	0.633	4.035	-69.813
Properties flooded in the year	other causes/M properties	0.544	-5.139	533.304
GWP of sewage treatment	kgCO2e /property connected for sewage	0.508	0.88	-21.657
Total company GWP	kgCO2e /property connected for water and sewage	0.485	3.89	-150.956
Spend on sewage treatment	£/property connected for S	0.471	1.632	-42.806
Sewage sub-total GWP	kgCO2e /property connected for sewage	0.466	2.048	-68.807
GWP of sewage collection	kgCO2e /property connected for sewage	0.46	1.041	-46.813
Water sub-total GWP	kgCO2e /property connected for water	0.427	1.45	-17.841
Employee total	number/M properties connected W+S	0.407	8.62	717.109

Indicator	**Unit**	**R2**	**Slope**	**Intercept**
Number of sewage treatment works	number/M property served S	0.823	24.008	-1508.89
Employee total	number/M properties connected W+S	0.407	8.62	717.109
Total length of section 105A sewers (km, 0 dp)	M/properties connected S	0.269	0.112	1.52
Total length of sewers (km, 0 dp)	M/properties connected S	0.147	0.059	8.88
Total number of service reservoirs	number/M properties served W	0.147	2.854	3.811
Total length of water mains (km, 0 dp)	M/properties connected W	0.062	0.081	9.358

Distribution input	Ml/d/M properties served W	0.061	-1.048	632.199
Total number of water treatment works	number/M properties served W	0.009	0.228	37.277
Indicator	**Unit**	**R2**	**Slope**	**Intercept**
Total load treated by STWs in size bands 1-3	kg BOD5/day/M properties	0.792	439.597	-27875.7
Properties flooded in the year	other causes/M properties	0.544	-5.139	533.304
Total number of S105A sewer blockages	number/M properties	0.386	164.312	-5665.25
Total number of rising main failures	number/M properties	0.334	18.807	-1327.36
Proportion of DI derived from impounding reservoirs	%	0.308	0.008	-0.312
Total number of gravity sewer collapses	number/M properties	0.261	3.288	-155.62
Total number of S105A gravity sewer collapses	number/M properties	0.226	5.294	-269.243
Mains bursts	number/thousand properties	0.219	0.031	-0.002
Properties below reference level at end of year	number/thousand properties	0.195	0.002	-0.055
Total load treated by all STWs	kg BOD5/day/M properties	0.165	1.847	-8.545
Total number of sewer blockages	number/M properties	0.127	85.29	-2263.74
Source types and pumping - total number of sources	number/thousand properties	0.107	0.001	-0.015
Properties flooded in the year	other causes - S105A/M properties	0.097	-1.682	232.661
Total length of mains renewed	number/thousand properties	0.047	-0.001	0.09
Proportion of DI derived from river abstractions	%	0.04	-0.003	0.604
Properties flooded in the year	overloaded sewers - S105A/M properties	0.022	0.073	-3.028
Source types and pumping - average pumping head	meters	0.005	0.145	121.293
Unplanned interruptions - more than 6 hours	number/thousand properties	0.001	0.043	9.517
Properties flooded in the year	overloaded sewers/M properties	0	0.021	34.161
Unplanned interruptions - more than 24 hours	number/thousand properties	0	-0.001	3.122
Unplanned interruptions - more than 12 hours	number/thousand properties	0	0.001	4.939
Indicator	**Unit**	**R2**	**Slope**	**Intercept**
GWP of sewage treatment	kgCO2e /property connected for sewage	0.508	0.88	-21.657
Total company GWP	kgCO2e /property connected for water and sewage	0.485	3.89	-150.956
Sewage sub-total GWP	kgCO2e /property connected for sewage	0.466	2.048	-68.807
GWP of sewage collection	kgCO2e /property connected for sewage	0.46	1.041	-46.813

Water sub-total GWP	kgCO2e /property connected for water	0.427	1.45	-17.841
GWP of water resources	kgCO2e /property connected for water	0.362	0.295	-9.123
GWP of water treatment	kgCO2e /property connected for water	0.251	0.867	-42.252
GWP of raw water distribution	kgCO2e /property connected for water	0.202	0.254	-12.121
GWP of sludge treatment	kgCO2e /property connected for sewage	0.029	0.129	-0.819
GWP of sludge disposal	kgCO2e/property connected for sewage	0.015	-0.002	0.482
GWP of treated distribution	kgCO2e/property connected for water	0.006	0.139	38.126

Appendix 2: Supplementary information to Chapter 4

2a. Full DEA efficiency tables

Economic

DMU	Non-Corrected	Non-corrected ranks	Bias-Corrected	Lower Bound	Upper Bound	Corrected ranks	Bias
14	1	1	1.285884	0.9796326	1.559158	1	-0.285884
13	1	2	1.523942	1.2535973	1.922438	2	-0.523942
11	1	3	1.873278	1.8349385	1.936331	3	-0.873278
15	1.599592	4	2.091618	1.7312727	2.454727	4	-0.492026
12	2.863947	5	3.761672	3.1345373	4.381939	5	-0.897725
17	3.589454	6	4.807255	4.0631957	5.57477	6	-1.217801
16	4.701992	7	6.259	5.2616529	7.275161	7	-1.557008
9	4.946775	8	6.545249	5.4782927	7.525034	8	-1.598474
6	5.678458	9	7.585141	6.3907295	8.779481	9	-1.906683
5	7.549739	10	10.063008	8.463406	11.706397	10	-2.513269
3	11.740985	11	16.219508	13.8586028	19.225166	11	-4.478523
1	11.954651	12	16.257079	13.8312175	19.059837	12	-4.302428
10	13.452771	13	18.515168	15.7321789	21.889963	13	-5.062397
2	14.694056	14	20.326007	17.3465921	24.11464	14	-5.631951
8	20.803997	15	29.170425	24.7235521	34.927064	15	-8.366428
4	22.242509	16	31.222113	26.3700218	37.411472	16	-8.979604
7	29.645859	17	42.467019	35.7452551	51.569211	17	-12.82116
Average	9.321457941		12.93960976	10.95286326	15.37134053		-3.618151824
SD	8.293917639		11.77252274	9.947253798	14.2366528		3.489153004

Energy

DMU	Non-Corrected	Non-corrected ranks	bias-corrected	Lower Bound	Upper Bound	Corrected ranks	Bias

14	1	1	1.286328	0.974914	1.552927	1	-0.28633
13	1	2	1.698021	1.554067	2.075919	2	-0.69802
11	1	3	1.835283	1.772028	2.010979	3	-0.83528
15	2.536182	4	3.267774	2.481617	3.935222	4	-0.73159
12	3.577397	5	4.685286	3.633626	5.605421	5	-1.10789
9	3.93109	6	5.168833	4.028337	6.181357	6	-1.23774
17	5.308747	7	7.051366	5.563718	8.446039	7	-1.74262
6	6.126873	8	8.342424	6.773443	9.998258	8	-2.21555
16	6.655122	9	9.009752	7.268139	10.80136	9	-2.35463
5	6.776251	10	9.201705	7.448491	11.0296	10	-2.42545
3	9.284371	11	13.46487	11.54483	16.03588	11	-4.1805
1	9.798978	12	13.75809	11.51317	16.4516	12	-3.95911
10	12.33366	14	17.91019	15.37028	21.33586	13	-5.57653
8	12.11606	13	18.1498	15.82768	21.7374	14	-6.03374
2	14.79384	15	21.40545	18.32279	25.4982	15	-6.6116
4	21.38579	16	32.27774	28.21388	38.69273	16	-10.892
7	22.76828	17	35.56793	31.56924	42.84031	17	-12.7997
Average	8.258391		12.005	10.22707	14.36641		-3.746
SD	6.462279		9.966	8.845456	11.96791		3.533

2b. Full primary and proxy indicator results

Economic

	Primary economic set		**CAPEX proxy**		**Volume of water produced proxy**	
Decision making units	**Bias-corrected estimates**	**Water utility rank**	**Bias-corrected estimates**	**Water utility rank**	**Bias-corrected estimates**	**Water utility rank**
14 (WoC)	1.286	1	1.577	2 (-1)	1.275	1
13 (WoC)	1.524	2	1.541	1 (+1)	1.47	2
11 (WoC)	1.873	3	1.715	3	1.854	3
15 (WoC)	2.092	4	1.72	4	2.07	4
12 (WoC)	3.762	5	3.4	5	2.806	5
17 (WoC)	4.807	6	4.243	6	3.674	6
16 (WoC)	6.259	7	6.147	8 (-1)	4.755	7
9 (WaSC)	6.545	8	5.958	7 (+1)	4.888	8
6 (WaSC)	7.585	9	7.437	10 (-1)	5.747	9
5 (WaSC)	10.063	10	6.965	9 (+1)	7.7	10
3 (WaSC)	16.22	11	13.413	11	12.745	12 (-1)
1 (WaSC)	16.257	12	14.07	12	12.508	11 (+1)
10 (WaSC)	18.515	13	16.471	13	14.623	13
2 (WaSC)	20.326	14	20.146	15 (-1)	16.064	14
8 (WaSC)	29.17	15	22.199	16 (-1)	23.845	15
4 (WaSC)	31.222	16	24.661	17 (-1)	25.783	16
7 (WaSC)	42.467	17	17.059	14 (+3)	35.725	17

Energy

	Primary energy set		**Volume of water produced proxy**	
Decision making units	**Bias-corrected estimates**	**Water utility rank**	**Bias-corrected estimates**	**Water utility rank**
14 (WoC)	1.286	1	1.288	1
13 (WoC)	1.698	2	1.706	2

11 (WoC)	1.835	3	1.841	3
15 (WoC)	3.268	4	3.262	4
12 (WoC)	4.685	5	4.712	5
9 (WaSC)	5.169	6	5.202	6
17 (WoC)	7.051	7	7.124	7
6 (WaSC)	8.342	8	8.383	8
16 (WoC)	9.01	9	9.107	9
5 (WaSC)	9.202	10	9.366	10
3 (WaSC)	13.465	11	13.535	11
1 (WaSC)	13.758	12	13.779	12
10 (WaSC)	17.91	13	18.167	13
8 (WaSC)	18.15	14	18.495	14
2 (WaSC)	21.405	15	21.61	15
4 (WaSC)	32.278	16	32.989	16
7 (WaSC)	35.568	17	35.99	17

Appendix 3: Supplementary Information to Chapter 5

3a. Full model variation results

Input: TOTEX								
Output: Water delivered and treated								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.989	-1.11%		0.963	-3.73%		1.027	2.73%
2015/16	1.169	16.94%		1.182	18.19%		0.989	-1.06%
2016/17	0.954	-4.60%		0.963	-3.73%		0.991	-0.90%
2017/18	0.923	-7.69%		0.906	-9.36%		1.018	1.84%
2018/19	1.008	0.77%		0.967	-3.32%		1.042	4.23%
Average		0.86%			-0.39%			1.37%
Input: TOTEX								
Output: Water supply + wastewater treated, renewables, customer satisfaction								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.996	-0.44%		0.995	-0.50%		1.002	0.24%
2015/16	1.23	22.98%		1.057	5.71%		1.176	17.60%
2016/17	0.952	-4.82%		0.945	-5.47%		1.006	0.62%
2017/18	0.945	-5.54%		0.958	-4.19%		0.987	-1.31%
2018/19	0.969	-3.07%		1.044	4.40%		0.931	-6.86%
Average		1.82%			-0.01%			2.06%
Input: TOTEX								
Output: Renewables, customer sat								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.993	-0.72%		0.985	-1.51%		1.01	0.96%
2015/16	1.264	26.38%		0.981	-1.87%		1.292	29.22%

2016/17	0.951	-4.88%		0.951	-4.90%		0.999	-0.05%
2017/18	0.947	-5.32%		0.961	-3.86%		0.985	-1.51%
2018/19	0.963	-3.72%		1.06	5.95%		0.91	-9.05%
Average		2.35%			-1.24%			3.91%
Input: TOTEX								
Output: Leakage reduction, consumption per capita reduction								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.968	-3.17%		0.923	-7.71%		1.05	4.98%
2015/16	1.437	43.66%		1.328	32.85%		1.11	11.03%
2016/17	0.853	-14.69%		0.844	-15.56%		1.01	1.03%
2017/18	0.901	-9.91%		0.957	-4.26%		0.949	-5.07%
2018/19	1.084	8.41%		0.961	-3.89%		1.137	13.72%
Average		4.86%			0.29%			5.14%
Input: OPEX								
Output: Water delivered and WW treated								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.999	-0.14%		0.985	-1.53%		1.014	1.41%
2015/16	0.969	-3.13%		0.934	-6.61%		1.037	3.73%
2016/17	0.92	-7.95%		0.971	-2.86%		0.948	-5.24%
2017/18	0.979	-2.07%		0.93	-7.03%		1.053	5.34%
2018/19	0.975	-2.47%		0.988	-1.20%		0.987	-1.29%
Average		-3.15%			-3.85%			0.79%
Input: OPEX								
Output: Water supply + wastewater treated, renewables, customer satisfaction								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	1.008	0.77%		0.986	-1.39%		1.025	2.50%
2015/16	1.052	5.24%		1.055	5.54%		0.998	-0.22%
2016/17	0.922	-7.82%		0.848	-15.17%		1.089	8.94%
2017/18	1.018	1.81%		1.098	9.80%		0.932	-6.76%
2018/19	0.942	-5.77%		0.891	-10.90%		1.058	5.85%
Average		-1.15%			-2.43%			2.06%
Input: OPEX								
Output: Renewables, customer sat								
	dTFP	% Change		dTech	% Change		dTFPE	% Change

2014/15	1.003452	0.35%		0.971634	-2.84%		1.035903	3.59%
2015/16	1.071994	7.20%		1.071547	7.15%		1.001561	0.16%
2016/17	0.925356	-7.46%		0.822966	-17.70%		1.123851	12.39%
2017/18	1.022975	2.30%		1.126302	12.63%		0.909507	-9.05%
2018/19	0.931019	-6.90%		0.868746	-13.13%		1.071824	7.18%
Actual average percentage change		-0.90%			-2.78%			2.85%
Inputs: OPEX								
Outputs: CPC reduction, leakage reduction								
	dTFP	% Change		dTech	% Change		dTFPE	% Change
2014/15	0.983853	-1.61%		1.008759	0.88%		0.975547	-2.45%
2015/16	1.209561	20.96%		1.16974	16.97%		1.043901	4.39%
2016/17	0.852164	-14.78%		0.897334	-10.27%		0.949922	-5.01%
2017/18	0.94552	-5.45%		1.012774	1.28%		0.947872	-5.21%
2018/19	1.070074	7.01%		0.790658	-20.93%		1.361934	36.19%
Actual average percentage change		1.22%			-2.41%			5.58%

3b. Chosen model configuration raw data

Years	dTFP	dMP	dTFPE	dITE	dISE	dIME	dRISE	dISME	dRME
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2014	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2015	1.005344	0.96249	1.044524	1	1.052576	1	1.044524	1.044524	0.99235
2015	0.96377	0.961386	1.00248	1.066263	0.965527	1	0.940181	0.940181	0.973748
2015	1.003417	1.02802	0.976068	1	1	1	0.976068	0.976068	0.976068
2015	1.126131	1.113696	1.011166	1	1	1	1.011166	1.011166	1.011166
2015	1.063248	0.961139	1.106237	1.06831	0.99527	1	1.035502	1.035502	1.040424
2015	0.992776	0.997601	0.995163	1	1	1	0.995163	0.995163	0.995163

2015	0.71823	0.961815	0.746745	1	0.727358	1	0.746745	0.746745	1.026654
2015	1.038822	0.963225	1.078483	1.397829	0.684345	1	0.771541	0.771541	1.127417
2015	0.944629	1.103745	0.85584	1	1	1	0.85584	0.85584	0.85584
2015	1.078719	0.961422	1.122003	1.176994	0.923892	1	0.953279	0.953279	1.031808
2015	0.98613	0.963212	1.023793	1.064804	0.948768	1	0.961485	0.961485	1.013403
2015	1.02547	0.962044	1.065928	1.316202	0.923112	1	0.809852	0.809852	0.877306
2016	0.94522	0.953447	0.991371	1	0.761621	1	0.991371	0.991371	1.30166
2016	1.119421	0.945921	1.183419	0.885942	1.031932	1	1.335776	1.335776	1.294442
2016	1.332159	1.271722	1.047523	1	1	1	1.047523	1.047523	1.047523
2016	1.213835	1.115055	1.088588	1	1	1	1.088588	1.088588	1.088588
2016	1.124515	0.955175	1.177286	1.00077	0.925722	1	1.17638	1.17638	1.27077
2016	1.065074	1.290605	0.825251	1	1	1	0.825251	0.825251	0.825251
2016	1.650081	1.225706	1.346229	1	1.311409	1	1.346229	1.346229	1.026551
2016	1.53278	0.962086	1.593184	1	1.303112	1	1.593184	1.593184	1.2226
2016	1.062258	1.109739	0.957214	1	1	1	0.957214	0.957214	0.957214
2016	1.523881	0.949423	1.60506	1.227216	1.071234	1	1.307887	1.307887	1.220916
2016	1.030322	0.958232	1.075232	0.890456	1.078369	1	1.207507	1.207507	1.119753
2016	1.158058	0.947706	1.221959	0.845028	0.949726	1	1.446058	1.446058	1.522605
2017	1.097575	0.934519	1.174482	0.786372	1.412178	1	1.493545	1.493545	1.057619
2017	0.868911	0.930636	0.933674	0.898764	1.025923	1	1.038842	1.038842	1.012593
2017	0.982951	0.944958	1.040206	1	1	1	1.040206	1.040206	1.040206
2017	1.076143	0.96681	1.113086	1	1	1	1.113086	1.113086	1.113086
2017	0.851987	0.93213	0.914021	0.840132	1.019339	1	1.087949	1.087949	1.067308
2017	0.842774	0.951595	0.885643	1	0.984958	1	0.885643	0.885643	0.899168
2017	1.068849	0.990031	1.079612	1	1.030054	1	1.079612	1.079612	1.048113
2017	1.003208	0.920239	1.09016	1	1.028089	1	1.09016	1.09016	1.060375
2017	1.014718	0.980232	1.035182	1	1	1	1.035182	1.035182	1.035182
2017	0.811794	0.928973	0.873862	0.810277	1.024522	1	1.078473	1.078473	1.05266
2017	0.942952	0.930274	1.013628	1.141328	0.947671	1	0.888113	0.888113	0.937152
2017	0.85954	0.933534	0.920738	0.754968	1.163536	1	1.219572	1.219572	1.04816
2018	0.919484	0.964464	0.953363	1.271663	0.760601	1	0.749698	0.749698	0.985665
2018	0.903113	0.961216	0.939553	0.970081	1.007437	1	0.96853	0.96853	0.961381
2018	0.866185	0.94289	0.91865	1	1	1	0.91865	0.91865	0.91865
2018	0.925137	0.999633	0.925476	1	1	1	0.925476	0.925476	0.925476
2018	0.832617	0.960013	0.867298	0.900329	1.03034	1	0.963312	0.963312	0.934945
2018	1.049744	0.894011	1.174196	1	1.015272	1	1.174196	1.174196	1.156533
2018	1.020975	0.968945	1.053698	1	1.09682	1	1.053698	1.053698	0.960685
2018	1.002231	0.974827	1.028111	1	1.117346	1	1.028111	1.028111	0.920137
2018	0.902034	0.94289	0.95667	1	1	1	0.95667	0.95667	0.95667
2018	0.950681	0.964464	0.985709	1.090611	1.005688	1	0.903814	0.903814	0.898702
2018	0.990744	0.962416	1.029434	0.949976	1.010698	1	1.083642	1.083642	1.072172
2018	0.971857	0.961216	1.01107	1.133462	0.999003	1	0.892019	0.892019	0.89291
2019	1.022171	1.081513	0.945131	1	1.109326	1	0.945131	0.945131	0.851987
2019	0.998179	1.081166	0.923243	1.071093	0.987364	1	0.861964	0.861964	0.872995
2019	0.930664	1.021953	0.910672	1	1	1	0.910672	0.910672	0.910672
2019	0.89519	1.016071	0.881031	1	1	1	0.881031	0.881031	0.881031

2019	0.971172	1.081166	0.898264	0.972431	1.002513	1	0.923729	0.923729	0.921414
2019	1.128428	0.960144	1.17527	1	1	1	1.17527	1.17527	1.17527
2019	0.968171	1.013829	0.954965	1	1	1	0.954965	0.954965	0.954965
2019	0.97029	1.07723	0.900727	1	1.00223	1	0.900727	0.900727	0.898722
2019	0.960729	0.951772	1.009411	0.984556	0.995061	1	1.025245	1.025245	1.030334
2019	0.816826	1.0809	0.75569	0.858429	1.00004	1	0.880318	0.880318	0.880283
2019	0.998177	1.080969	0.92341	0.921373	1.002268	1	1.00221	1.00221	0.999942
2019	0.971738	1.081166	0.898788	1.074521	0.98953	1	0.836454	0.836454	0.845304

3c. Chosen model configuration full results breakdown

	dTFP	% Change	dTech	% Change	dTFPE	% Change	dITE	% Change	dISE	% Change	dRISE	% Change	dRME	% Change
2014/15	0.996	-0.44%	0.995	-0.50%	1.002	0.24%	1.091	9.09%	0.935	-6.49%	0.925	-7.49%	0.993	-0.66%
2015/16	1.230	22.98%	1.057	5.71%	1.176	17.60%	0.987	-1.25%	1.036	3.61%	1.194	19.36%	1.158	15.82%
2016/17	0.952	-4.82%	0.945	-5.47%	1.006	0.62%	0.936	-6.40%	1.053	5.30%	1.088	8.75%	1.031	3.10%
2017/18	0.945	-5.54%	0.958	-4.19%	0.987	-1.31%	1.026	2.63%	1.004	0.36%	0.968	-3.18%	0.965	-3.47%
2018/19	0.969	-3.07%	1.044	4.40%	0.931	-6.86%	0.990	-0.98%	1.007	0.74%	0.941	-5.85%	0.935	-6.48%
Average		1.82%		-0.01%		2.06%		0.62%		0.70%		2.32%		1.66%

Appendix 4: Supplementary information for Chapter 6

4a. Core sample for wastewater energy intensity (kWh/m^3) for companies treating at least 95% at secondary treatment level of better

		kWh_m3_ww					Size (population served)
Country	**Company**	**2014**	**2015**	**2016**	**2017**	**2018**	
Belarus	Baranovichy Communal Unitary Manufacturing Enterprise "Vodokanal" [BY6]		0.44	0.45		0.51	179,000
	Bobruisk State Enterprise "Vodokanal" [BY20]		0.34	0.3		0.33	217,546
	Borisov Unitary Enterprise Vodokanal [BY11]					0.4	181,100
	Communal Manufacturing Unitary Enterprse "Brestvodokanal" [BY7]		0.83	0.41		0.44	350,616
	Communal Unitary Enterprise "Smolevichi Housing and Utilities" [BY38]		0.4	0.4		1.18	46,230
	Communal Unitary Manufacturing Enterprise "Pinskvodokanal" [BY36]		0.51	0.75			143,330
	Communal Unitary Multisectoral Manufacturing Enterprse "Gantsevichy District Housing and Utilities" [BY29]		0.8	0.78		0.77	9,504
	Communal Utility Enterprise of Housing and Utilities of Sharkovschina region [BY39]			1.48			6,420
	Dokshytsy Department of Vitebsk Communal Unitary Enterprise Vodokanal [BY54]					2.15	328,700
	Logoisk communal services company [BY58]					0.3	35,630
	Mogilev Municipal Communal Unitary Enterorise "Gorvodokanal" [BY10]		0.51	0.51		0.41	383,300
	Multi-industry communal enterprise Ivanovo [BY51]					1.59	36,235
	Municipal Regional Unitary Enterpise on Housing and Utility "Gorodok" [BY31]		0.64			0.93	37,000
	Oshmyany District Communal Utility [BY52]					1.28	17,400
	Regional Communal Services Company Pukhovichskii District Minsk Oblast [BY23]			0.66		0.61	208,660
	Senno Regional Unitary Enterprise on Housing and Utilities [BY25]					1.3	8,360
	Shklov Unitary Communal Enterprise "Zhilkomhoz" [BY17]					1.95	27,900
	Slutskvodokanal [BY59]					1.25	91,060
	Soligorskvodokanal [BY60]					0.54	132,640
	Svisloch District Communal Utility [BY53]					0.93	6,430
	Unitary Enterprise of Housing and Utilities "Dubrovno-Kommunal'nik" [BY32]		1.92	2.33			12,378

	Unitary Enterprise of Housing and Utilities of Usvizh District [BY56]					1.3	500
Norway	Bergen [811]			0.81			277,500
	Oslo kommune [7941]		0.27	0.32	0.85	0.78	679,500
	Trondheim [8199]			0.80	0.2	0.29	189,064
Switzerland	Services industriels de Genève [CH1]		0.57	0.57			265,000
Denmark	Aarhus Vand A/S [DK2]		0.81			1.25	259,133
	VCS Denmark [DK1]		1.98			1.6	166,500
	Vejle					1.52	113,720
	Horsens					0.77	90,370
	Fredericia					2.25	50,429
	DINForsyning					1.56	166,000
	Randers					1.27	96,559
	Horsholm					0.81	47,499
	Herning					1.92	50,332
	Koge					1.19	60,675
	Mariagerfjord					1.1	30,000
	AquaDjurs					1.72	37,558
	Billund					1.79	22,240
	Kerteminde					0.79	23,756
	Sonderborg					0.93	74,650
	Odder					0.76	7,919
	Fr. Havn					1.69	52,127
	Rudersdal					0.78	55,412
	Skanderborg					0.82	56,402
	Hjorring					1.32	52,000
	Lolland					0.84	19,580
	Syddjurs					1.36	35,100
	Bornholm					0.94	30,000
	Viborg					1.07	97,113
	NFS A/S					2.17	36,166
	Greve					0.9	49,895
	Skive					0.9	15,955
	Middelfart					1.08	38,553
	Fors Holbaek					1.21	60,676
	Tarnby					1.06	43,063
	HOFOR Dragor					0.98	12,309
	Bronderslev					0.99	28,000
	Slagelse-Kor					1.89	34,015
	Vestforsyning					1	52,000
	Ikast-Brande					1.01	36,000
	Silkeborg					1.52	83,890
	Malov					1.16	8,797
	Ringsted					1.06	28,640
	BIOFOS SCA					1.29	253,091
	Allerod					1.29	24,418
	FFV					1.09	51,735

	Provas					1.07	50,815
	Solrod					1.08	23,000
	Fredensborg					1.1	40,513
	Jammerbugt					1.1	45,700
	Stevns					1.1	19,217
	Molleavaerket					2.06	150,000
	Struer					1.13	19,083
	Halsnaes					1.33	28,450
	Fors Roskilde					1.36	85,549
	Favrskov					1.26	42,200
	Morso					1.28	15,970
	Tonder					1.29	29,497
	Hedensted					1.4	33,350
	Thisted					1.82	52,405
	Odsherred					1.32	26,100
	Lemvig					1.34	19,200
	Soro					1.42	21,000
	Ringk. Skj					1.45	41,000
	Langeland					1.37	9,119
	Svendborg					1.61	57,560
	Arwos					1.68	49,600
	Egedal					1.51	41,495
	Naestved					2.27	43,803
	Assens					1.55	34,915
	Gribvand					1.55	48,163
	Fors Lejre					1.58	25,040
	Fr. Sund					1.6	41,744
	V. Himmerland					1.78	29,530
	Fureso					2.64	40,586
	Rebild					2.12	23,000
UK	Dwr Cymru Welsh Water [GB2]				0.55	0.51	3,030,618
	Yorkshire Water [GB1]		1.03		1.16	1.13	4,979,631
	Anglian				0.83	0.79	6,000,000
	Northumbrian				0.84	0.83	4,400,000
	Severn Trent				0.47	0.50	8,000,000
	Southern				1.27	1.31	4,600,000
	South West				0.76	0.74	1,700,000
	Thames				0.68	0.68	15000000
	United Utilities				0.46	0.45	7,000,000
	Wessex				1.38	0.78	2,800,000
Croatia	Koprivničke vode d.o.o. Koprivnica [CR6]		0.58				51,668
Poland	Aquanet S.A.,Poznań [PL18]		1.05				761,112

	MPWiK S.A. we Wrocławiu,Wrocław [PL38]		0.72				635,759
Ukraine	Chernigiv Water and Sewerage Enterprise [UA18]		0.65				297,865
	Communal enterprise Ternopol Vodokanal [UA5]		1.31				245,799
	Communal Enterprise Vodokanal of Melitopol City Council of Zaporizhzhya region [UAN5]		1.17				125,724
	Communal Enterprise “Kremenchukvodokanal” of Kremenchuk City Council [UAN2]		0.62				189,000
	Ivano-Frankivskvodoekotekhprom Utility [UAN6]		0.62				283,573
	Novomoskovsk Water and Sewerage Department of Dnipropetrovsk Municipal Enterprise "Oblvodokanal" [UA9]		0.97				75,300
	Rivne Oblast Municipal Water and Sewer Enterprise [UA9]		0.71				293,030
	Utility Ilichevskvodokanal [UAN1]		0.77				75,556
	CE “Boryspilvodokanal” [UAN3]		0.28				60,900
Moldova	Integrated Communal Services Company Faleşti [MD19]			0.99	0.75		15,600
	Integrated Communal Services Company Glodeni [MD22]			0.83	0.52		10,500
	Integrated Communal Services Company Lipcani [MD25]			2.20	1.86		5,100
	Integrated Communal Services Company Ocnita [MD27]			0.63	0.55		9,236
	Integrated Communal Services Company Otaci [MD29]			0.48	0.58		7,400
	Municipal enterprise Apa Canal Anenii Noi [MD1]			0.97	0.76		13,000
	Municipal Enterprise Apa Canal Cahul [MD5]			0.49	0.45		48,300
	Municipal Enterprise Apa Canal Drochia [MD17]			0.43	0.70		17,500
	Municipal Enterprise Apa Canal Edineti [MD18]			1.73	1.17		25,800
	Municipal Enterprise Apa Canal Stefan-Vodă [MD36]			0.24	0.18		7,400
	Municipal Enterprise Apa Canal Taraclia [MD38]			0.93	0.82		12,300
	Municipal Enterprise Apa Canal Teleneşti [MD39]			0.54	0.56		8,600
	Municipal Enterprise Apa Canal Vulcaneşti [MD41]				0.52		16,700
	Municipal Enterprise Communservice Criulni [MD15]			0.49	0.43		9,700
	Municipal Enterprise Company Apa Canal Riscani [MD31]			0.57	0.82		13,500
	Municipal Enterprise Şoldăneşti-Service [MD33]			0.54	0.64		6,100
	S.A. Regia Apă-Canal Chişinău [MD1]			0.44			842,500
Hondurus	Aguas de Puerto Cortés, S.A. de C.V. [9995]	0.64					82,327
Nigeria	Rivers State Water Board [NG28]	0.22	0.77	0.74			1,005,908
Bosnia	AD Vodovod I Kanalizacija Bijeljina [BH6]	0.47	0.18	0.10	0.43	0.87	114,663
	JP Vodovod a.d. Trebinje [BH2]		0.38	0.41	0.41	0.41	29,198
	Javno poduzeće Broćanac d.o.o. Čitluk [BH66]	1.28					18,820
Serbia	D.o.o. Standard Komunalno preduzeće Stara Moravica [8687617]		0.04	0.05			5,100
	Doo "Potiski Vodovodi" Horgoš [825355]	0.87	0.74	0.83	0.81		23,961
	Društveno javno komunalno preduteće "Polet" [849599]		0.11		0.32		11,334
	Javno komunalno preduzeće "6. oktobar" Kikinda [83743]	0.93					59,329
	Javno komunalno preduzeće "Gornji Milanovac" [7192819]	0.30	0.17	0.26			48,500

	Javno komunalno preduzeće "Vodovod i kanalizacija" Subotica [865195]	0.56	0.72	0.86	0.97		141,554
	Javno komunalno preduzeće "Vodovod Valjevo" [7136277]	0.23	0.23	0.23	0.16		100,000
	Javno komunalno preduzeće Elan Kovačica [87769]		2.40	0.74		1.15	6,165
	Javno komunalno preduzeće Progres [8198748]				3.50	2.72	8,500
	Javno komunalno preduzeće Miloš Mitrović Velika Plana [716763]	0.77	0.74	0.93	1.21		40,902
	Javno preduzece Vodokanal Becej [869921]	0.56	0.61	0.59	0.57		36,187
	Javno preduzeće "Vodovod" Surdulica [71811]	0.04	0.04	0.04	0.05		18,930
	Javno preduzeće Komunalac Dimitrovgrad [7299974]		0.14	0.20			9,623
	Javno preduzeće za komunalno-stambenu delatnost [7114885]			0.17	0.21		70,000
	JKP "Drugi oktobar" Vršac [8171]			0.27	0.35		51,217
	JKP "Standard" Ada [81375]	1.27	1.14	1.13			16,093
	JKP "Vodokanal" Sombor [846751]	0.43	1.05	1.10	1.08		80,400
	JKP "Vodovod" Šabac [7168683]	0.15	0.81	0.64	0.37		122,843
	JKP vodovod i kanalizacija Pećinci [2585439]				0.45		19,283
	JKSP Opština Topola [7123852]	1.03	0.69	1.08			25,000
	JP Polet Plandište [8495]			0.22			11,334
	JP za komunalnu infrastrukturu i usluge Kikinda [2171986]			1.10	0.61		55,318
	Komunalno javno preduće "Morava" Svilajnac [7253931]	0.27	1.11	0.36	0.40	0.34	23,551
	Preduzeće u društvenoj svojini za komunalnu delatnost Vršac [8172]	0.32	0.36				51,217
Macedonia	Berovo Public Utility Works Usluga [MC9]	0.30	0.33				12,714
	Ilinden Water Company Vodovod [MC2]	0.49	0.85				15,894
	Makedonski [MC15]	0.21					7,203
	Public Enterprice "Vodovod" Kumanovo [MC15]	0.22	0.16	0.15			115,000
Russia	Barnaul,OOO "Barnaulskiy Vodokanal" [26]			0.88			651,002
	Belgorod,MUE "Gorvodokanal" [27]			0.98			389,112
	Birobidzhan,MUE "Vodokanal" [28]			0.37			74,327
	Blagoveschensk,JSC "Amurskie kommunalnie sistemy" [29]			0.65			224,377
	Bryansk,MUE "Bryanskiy gorodskoy vodokanal" [21]			0.75			406,237
	Chelyabinsk,MUE "PO vodosnabzheniya I vodootvedeniya" [212]			0.73			1,195,426
	Cherkessk,JSC "Vodokanal" [213]			0.78			122,803
	Chita,OOO "Vodokanal-Chita" [214]			0.75			345,299
	Ekaterinburg,MUE "Vodokanal" [216]			0.57			1,449,977
	Elista,MUE "Gorvodokanal" [217]			0.32			103,952
	Gorno-Altaysk,JSC "Vodokanal" [218]			0.83			63,078
	Irkutsk,MUE "PU VKH" [219]			0.59			623,580
	Ivanovo,JSC "Vodokanal" [22]			0.54			407,479
	Izhevsk,MUE "Izhvodokanal" [221]			0.84			644,887
	Kaluga,OOO "Kaluzhskiy oblastnoy vodokanal" [223]			0.41			341,939
	Kazan,MUE "Vodokanal" [224]			0.77			1,224,422
	Kemerovo,OOO "Kemvod" [225]			1.11			554,998
	Khabarovsk,MUE "Vodokanal" [226]			0.75			613,701
	Khanty-Mansiysk,MUE "Vodokanalizatsionnoe predpriyatie" [227]			1.37			97,814

	Kirov,JSC "Kirovskie kommunalnie sistemy" [228]			0.95			499,227
	Kostroma,OOO "Kostroma Vodokanal" [229]			0.78			277,170
	Krasnodar,OOO "Krasnodar Vodokanal" [23]			0.87			867,662
	Krasnoyarsk,OOO "Krasnoyarskiy zhilischno-kommunalniy kompleks" [231]			0.84			1,074,934
	Kurgan,MUE "Kurganvodokanal" [233]			1.00			323,616
	Kursk,MUE "Vodokanal goroda Kurska" [234]			0.81			446,137
	Kyzyl,OOO "Vodoprovodno-kanalizatsionnie sistemy" [235]			0.37			115,943
	Lipetsk,JSC "Lipetskaya gorodskaya energeticheskaya kompaniya" [236]			0.49			510,230
	Maikop,MUE "Maikopvodokanal" [238]			0.88			168,918
	Moscow,MSUE "Mosvodokanal" [24]			0.51			########
	Nalchik,ME "Gorvodokanal" [242]			0.29			278,593
	Naryan-Mar,"Naryan-Mar Vodokanal" [243]			1.01			24,595
	Nizhni Novgorod,JSC "Nizhegorodskiy Vodokanal" [245]			0.46			1,264,269
	Novgorod,MUE "Novgorodskiy Vodokanal" [246]			0.87			222,231
	Novosibirsk,MUE "Gorvodokanal" [247]			0.78			1,774,044
	Omsk,JSC "OmskVodokanal" [248]			0.95			1,178,235
	Orenburg,OOO "Orenburg Vodokanal" [249]			0.28			577,622
	Oryol,MUE "Orelvodokanal" [25]			0.77			319,142
	Penza,OOO "Gorvodokanal" [252]			1.02			524,179
	Perm,OOO "Novogor-Prikamye" [RU 57]			0.89			1,044,941
	Petrozavodsk,JSC "Petrozavodskie kommunalnie sistemy" [RU 78]			0.81			277,831
	Pskov,MUE "Gorvodokanal" [256]			0.93			225,207
	Rostov-na-Donu,JSC "PO Vodokanal" [257]			0.69			1,122,587
	Ryazan,ME "Vodokanal goroda Ryazani" [258]			2.24			536,192
	Samara,ME "Samaravodokanal" [26]			0.47			1,182,425
	Saransk,ME "Saranskgorvodokanal" [261]			0.75			311,244
	Saratov,MUE "Saratovvodokanal" [262]			0.78			863,585
	Smolensk,MUE "Gorvodokanal" [263]			0.62			329,380
	Stavropol,SUE "Stavropolkraivodokanal" [265]			0.62			431,574
	Tambov,JSC "Tambovskie kommunalnie sistemy" [267]			0.80			391,951
	Tomsk,OOO "Veolia Voda Tomsk" [268]			1.75			571,017
	Tula,JSC "Tulagorvodokanal" [269]			0.49			651,408
	Tver,OOO "Tver Vodokanal" [271]			1.04			417,902
	Tyumen,OOO "Tyumen Vodokanal" [272]			0.60			732,565
	Ufa,MUE "Ufavodokanal" [273]			1.12			1,113,268
	Ulyanovsk,MUE "Ulyanovskvodokanal" [275]			1.21			628,605
	Vladikavkaz,OOO "Sevosetinvodokanal" [277]			0.04			307,228
	Vladimir,MUE "Vladimirvodokanal" [278]			0.75			355,497
	Volgograd,MUE "Gorvodokanal Volgograda" [28]			1.33			1,015,861
	Vologda,ME "Vologdagorvodokanal" [281]			0.79			312,849
	Yakutsk,JSC "Vodokanal" [283]			1.02			305,874
	Yaroslavl,JSC "Yaroslavlvodokanal" [284]			0.93			607,391
	Yoshkar-Ola,MUE "Vodokanal" [285]			0.68			265,860
	Yuzhno-Sakhalinsk,OOO "Sakhalinskiy Vodokanal" [286]			0.75			194,276

Kazakhstan	JSC Kyzylzhar Su, Petropavlovsk [KZ22]		0.77	0.78			215,306
	JSC Pavlodar Vodokanal [KZ13]		0.62	0.65			358,800
	JSC Vodnye Resursy Marketing, Shymkent [KZ14]		0.15	0.13			893,800
	Karaganda Su Limited Liability company [KZ2]		1.26	1.23			499,615
	Open JSC Akbulak, Aqtobe [KZ15]		1.16	1.12			478,000
	State Communal Enterprise Astana Su Arnasy [KZ1]		0.69	0.21			1,000,000
	State Communal Enterprise Gorvodokanal Ekibastuz [KZ19]		0.99	1.03			155,681
	State communal Enterprise Infroservice, Ridder [KZ9]		0.30	0.31			58,049
	State communal Enterprise Kokshetau Su Arnasy [KZ7]		0.89	0.93			159,490
	State communal Enterprise Kyzylorda Su Zhuiyesi [KZ2]		0.81	0.89			297,300
	State communal Enterprise Oskemen Vodokanal Ust Kamenogorsk [KZ1]		0.50	0.53			331,814
	State Communal Enterprise Semei Vodokanal, Semipalatinsk [KZ5]		0.65	0.78			344,500
	State Enterprise Vodokanal Zyryanovsk [KZ16]		0.70	0.69			39,859
	State Enterprize Saran Kommun Service [KZ9]		0.26	0.22			52,900
	Stepnogorsk State Municipal Company Vodokanal [KZ2]		1.73	1.86			52,450
New Zealand	Ashburton District Council [NZ2]		0.53	0.60	0.65	0.56	34,100
	Christchurch City Council [NZ7]		0.30	0.45	0.22	0.22	381,500
	Gore District Council [NZ11]		0.29	0.24	0.30		12,450
	Hamilton City Council [NZ15]		1.02	1.25	1.09	1.14	165,400
	Hutt City Council [NZ3]		1.54	1.41	1.75		54,800
	New Plymouth District Council [NZ21]		0.50	1.88	1.72	1.64	80,700
	Palmerston North City Council [NZ22]		1.53	0.27	0.52	0.34	87,300
	Stratford District Council [NZ58]			0.17			36,800
	Tauranga City Council [NZ29]		0.81	0.72	0.80	0.59	47,100
	Waimakariri District Council [NZ37]		1.23	1.17	1.04	0.91	30,000
	Waimate District Council [NZ59]			0.11			7,536
	Wellington		0.67	0.68	0.56	0.70	416,700
	Whakatane					0.35	35,600
	Nelson					0.29	51,400
	Napier					0.25	62,000
	Rotorua				1.16	1.17	59,300
	Invercargill			0.14	0.2	0.36	22,500
	Western Bay of Plenty					1.45	49,000
	Masterton				0.12	0.10	25,200
	Ruapehu					0.56	28,000
	Marlborough District Council [NZ2]		0.67	0.75			45,500
	Rangitki District Council [NZ1]				0.51		12,700
	South Wairarapa District Council [NZ56]			0.23			10,250
	Wairoa District Council [NZ39]		0.29	0.29	0.27		8,150
	Watercare, Auckland [NZ1]		0.48	0.51	0.79	0.91	1,665,809
	Whangarei Distrcit Council [NZ36]		0.36	0.18	0.14	0.33	89,700
Federated States Of Micronesia	Chuuk Public Utilities Corporation, Micronesia [PWWA4]		0.43	0.34	0.45	0.45	13,856
French Polynesia	Polynésienne des Eaux [PWWA5]		0.85	0.58	0.62	0.56	91,056

Palau	Palau Public Utilities Corporation (PPUC), Palau [PWWA14]			0.41			17,661
Samoa	Samoa Water Authority [PWWA18]			1.3	1.37	1.53	197,023
Australia	Barwon Water				0.13		312,235
	Central Gippsland Region Water Corporation					0.55	147,000
	Central Highlands Water				0.77		146,568
	Coliban Region Water Corporation				1.26	1.21	170,000
	East Gippsland Region Water Corporation				0.68	0.71	35,000
	Goulburn Valley Region Water Corporation	0.52	0.62	0.53	0.60	0.56	125,000
	Grampians Wimmera Mallee Water Corporation	0.54	0.64	0.55	0.60	0.68	72,000
	Hunter Water Corporation	0.58	0.63				600,000
	Melbourne Water Corporation					0.33	4,200,000
	North East Region Water Corporation				1.23	1.17	109,803
	South East Water Corporation					0.23	778,018
	South Gippsland Region Water Corporation	0.67	0.66	0.62	0.65	0.62	36,819
	Wannon Water				1.00	0.96	100,400
	Water Corporation	0.80	0.81	0.87	0.91	0.84	2,600,000
	Western Region Water Corporation				1.02	1.04	172,500
	Westernport Water Corporation					1.50	22,000
	Yarra Valley Water Corporation				0.14	0.13	2,100,000
Belgium	Aquafin NV [BE2]		1.14				3,800,000
Fiji	Water Authority of Fiji [PWWA3]	0.31	0.26	0.28	0.36	0.34	895,537
Netherlands	Aa en Maas		0.935138				744,000
	Amstel, Gooi en Vecht		0.917034				1,300,000
	Brabantse Delta		1.13902				800,000
	De Dommel		0.892003				890,000
	De Stichtse Rijnlanden		1.227425				750,000
	Delfland		1.230202				1,400,000
	Fryslân		0.968046				700,000
	Hollands Noorderkwartier		1.38505				1,161,000
	Hollandse Delta		0.896253				850,000
	Hunze en Aa's		0.923395				424,000
	Noorderzijlvest		0.896143				345,000
	Rijn en IJssel		1.334159				650,000
	Rijnland		0.935995				1,248,124
	Rivierenland		0.992197				1,043,000
	Scheldestromen		0.94586				383,112
	Schieland en de Krimpenerwaard		0.860264				657,665
	Vallei en Veluwe		1.201045				1,120,000
	Vechtstromen		1.086738				825,000
	Zuiderzeeland		1.33633				416,431
Greece	Athens Water Supply and Sewerage Company SA				0.584464		3,500,000
Italy	Società Metropolitana Acque Torino S.p.A.				0.278592	0.266805	2,247,449

Spain	Canal de Isabel II				0.571397		6,370,090
Sweden	VA SYD	0.505	0.5125	0.5525			500,000
Canada	City of Toronto				0.513816		2,876,700
United States	King County					0.621871	1,870,000

4b. External Sample

Country	kWh/m^3	Source
Japan	0.53	10.1007/s10098-016-1131-1
Portugal	0.37	doi.org/10.1016/j.jclepro.2018.12.229
Mexico	1.15	https://doi.org/10.1016/j.scitotenv.2017.02.234
Brazil	0.24	BRASIL. Ministério das Cidades. Sistema Nacional de Informações sobre Saneamento (SNIS), Diagnóstico dos Serviços de Água e Esgotos - 2014, 2016.
South Africa	0.2445	doi.org/10.1016/j.apenergy.2016.07.061
India	0.24	http://www.iaeme.com/ijciet/issues.asp?JType=IJCIET&VType=10&IType=9
Singapore	0.56	https://doi.org/10.1016/j.scitotenv.2011.04.018
South Korea	0.243	doi.org/10.1016/j.enconman.2013.08.028
Finland	0.49	https://doi.org/10.1007/s40710-018-0310-y
Germany	0.43	doi.org/10.1016/j.apenergy.2016.07.061
China	0.3	doi.org/10.1016/j.apenergy.2016.07.061

4c. Wastewater effluent standards

Country/Region	**WWTP category**	**COD (mg/l)**	**BOD_5 (mg/l)**	**NH_4^+-N, NH_3-N (mg/l)**	**NO_2^-–N, NO_3^-–N (mg/l)**	**Total Nitrogen (mg/l)**	**PO_4^{3}–P (mg/l)**	**Total Phosphorus (mg/l)**	**Total Suspended Solids (mg/l)**	**Source**
EU	<2000 PE	125	25	n/n[a]	n/n	n/n	n/n	n/n	35	EC (1991) Council Directive 91/271/EEC of 21 May 1991 concerning urban waste-water treatment. EC, Brussels, Belgium
	2000–10,000 PE	125	25	n/n	n/n	n/n	n/n	n/n	35	
	10,000–100,000 PE	125	25	n/n	n/n	15 (areas sensitive to	n/n	2 (areas sensitive to	35	

						eutrophication)		eutrophication)		
	>100,000 PE	125	25	n/n	n/n	10 (areas sensitive to eutrophication)	n/n	1 (areas sensitive to eutrophication)	35	
Germany	BOD_5 < 60 kg/d (<1000 PE)	150	40	n/n	n/n	n/n	n/n	n/n	n/n	Federal Ministry of Environment Nature Conservation and Nuclear Safety (2002) Federal Water Act of 19 August 2002. Federal Law Gazette. Federal Ministry of Environment Nature Conservation and Nuclear Safety, Bonn, Germany
	BOD_5 < 300 kg/d (<5000 PE)	110	25	n/n	n/n	n/n	n/n	n/n	n/n	
	BOD_5 < 1200 kg/d (<20,000 PE)	90	20	10	n/n	n/n	n/n	n/n	n/n	
	BOD_5 < 6000 kg/d (<100,000 PE)	90	20	10	n/n	18	n/n	2	n/n	
	BOD_5 < 6000 kg/d (>100,000 PE)	75	15	10	n/n	13	n/n	1	n/n	
Sweden	>2000 PE	n/n	15[b] (BOD_7)	n/n	n/n	15	n/n	0.5	n/n	Swedish EPA (2016) Wastewater treatment in Sweden 2016. Swedish EPA
	2000–100,000 PE	n/n	15 (BOD_7)	n/n	n/n	15	n/n	0.5	n/n	
	>100,000 PE	n/n	15 (BOD_7)	n/n	n/n	10	n/n	0.5	n/n	
Denmark	General	75	10	n/n	n/n	8	n/n	0.4	20	Vind J (2017) Wastewater innovation in Denmark - Water technology alliance a report by the ministry of foreign affairs of Denmark, Copenhagen
HELCOM signatory countries	300–2000 PE	n/n	25	n/n	n/n	35	n/n	2	35	HELCOM (2007) HELCOM recommendation 28E/5. HELCOM, Helsinki, Finalnd; https://helcom.fi/media/publications/Technical-

										guidance-for-the-handling-of-wastewater-in-ports.pdf
	2000–10,000 PE	125	15	n/n	n/n	30	n/n	1	35	
	10,000–100,000 PE	125	15	n/n	n/n	15	n/n	0.5	35	
	>100,000 PE	125	15	n/n	n/n	10	n/n	0.5	35	
Switzerland	200–10,000 PE	60	20	2 (sum of NH_3–N and NH_4–N)	0.3 (NO_2^-–N)	0.8	0.8	n/n	20	The Swiss Federal Council (1998) Waters Protection Ordinance (814.201) of 28 October 1998. The Swiss Federal Council, Bern, Switzerland
	>10,000 PE	45	15	2 (sum of NH_3–N and NH_4–N)	0.3 (NO_2^-–N)	0.8	0.8	n/n	15	
Belarus	<500 PE	125	35	n/n	n/n	n/n	n/n	n/n	n/n	Ministry of Environment (2012) Technical code of practice (in Russian). Ministry of Environment, Moscow, Russia
	501–2000 PE	120	30	20	n/n	n/n	n/n	n/n	n/n	
	2001–10,000 PE	100	25	15	n/n	n/n	n/n	n/n	n/n	
	10,001–100,000 PE	80	20	n/n	n/n	20	n/n	4.5	n/n	
	>100,000 PE	70	15	n/n	n/n	15	n/n	2	n/n	
USA	n/n	n/n	30	6.8	n/n	3–5 (areas sensitive to eutrophication)	n/n	1.0–0.1 (areas sensitive to eutrophication)	n/n	Sedlak RI (1991) Phosphorus and nitrogen removal from municipal wastewater: principles and practice. The Soap and Detergent Association, New York, USA; US EPA (2012) Great lakes water quality agreement. https://doi.org/10.1016/j.apenergy.2016.07.061 13–31. https://doi.org/10.1016/b978-0-08-020902-9.50006-7
China (Taihu Lake catchment)	n/n	50	n/n	8 (NH_4^+–N, 5 in winter season)	n/n	15	n/n	0.5	n/n	Li WW, Sheng GP, Zeng RJ et al. (2012) China's wastewater discharge

										standards in urbanization: evolution, challenges and implications. Environ Sci Pollut Res 19:1422–1431. https://doi.org/10.1007/s11356-011-0572-7
BC, Canada	Streams, rivers and estuaries	n/n	45 (10 if dilution ratio < 40:1)	n/n	n/n	10	0.5 (MDF[c] > 50 m^3/d)	1.0 (MDF > 50 m^3/d)	45	British Columbia Office of Legislative Counsel Ministry of Attorney General (2005) Environmental Management Act Municipal Wastewater Regulation B.C. Reg. 87/2012. British Columbia Office of Legislative Counsel Ministry of Attorney General, Victoria, Canada; US EPA (2012) Great lakes water quality agreement. 13–31. https://doi.org/10.1016/b978-0-08-020902-9.50006-7
	Lakes	n/n	45	n/n	n/n	10	0.5 (MDF > 50 m^3/d)	1.0 (MDF > 50 m^3/d)	45	
	Open marine water	n/n	130 (MDF > 10 m^3/d)	n/n	n/n	n/n	n/n	n/n	60	
	Coastal waters	n/n	45 (MDF > 10 m^3/d)	n/n	n/n	n/n	n/n	n/n	45	
Russia	Industrial fishing areas	n/n	3.0[d] (BOD_{20})	0.39	0.02 (NO_2^-–N) 9.1 (NO_3^-–N)	n/n	2.0 (0.2 in eutrophic waters, 0.15 in mesotrophic waters, 0.05 in oligotrophic waters)	n/n	n/n	Ministry of Natural Resources (1991) Surface water protection act (in Russian). Ministry of Natural Resources, Moscow, Russia; Ministry of Natural Resources (1999) Surface water protection regulation (in Russian). Ministry of Natural Resources, Moscow,

										Russia; Gogina ES (2010) Udalenie biogennych elementow iż stocznych wod. Moskowskij gosudarstwiennyj stroitelnyj uniwersytet, Moscow, Russia
	Source of water supply	15	3.0 (BOD_{20})	n/n	n/n	n/n	n/n	n/n	n/n	
	Recreation and water sports	30	6.0 (BOD_{20})	n/n	n/n	n/n	n/n	n/n	n/n	
South Africa	Coastal waters, lakes	75	n/n	6	n/n	15	n/n	n/n	25	https://selectech.co.za/updated-effluent-waste-water-quality-standards/
	Rivers and dams	30	n/n	2	n/n	1.5	n/n	n/n	10	
Brazil	General	n/n	60	20	n/n	n/n	n/n	n/n	60	Standards for Wastewater Treatment in Brazil Marcos von Sperling
Nigeria	Varied	60-90	30-50	1	n/n	10	n/n	2	25	Management Recommendations for Improving Decentralized Wastewater Treatment by the Food and Beverage Industries in Nigeria
India	General	250	30	n/n	n/n	10	n/n	5	50-100	Management Recommendations for Improving Decentralized Wastewater Treatment by the Food and Beverage Industries in Nigeria
Australia (Tasmania)	Fresh	n/n	15	5	n/n	15	n/n	3	n/n	https://epa.tas.gov.au/Documents/Emission_Limit_Guidelines_June_2001.pdf
	Marine	n/n	20	5	n/n	15	n/n	5	n/n	
Australia (Queensland)	Surface	n/n	30	n/n	n/n	15	n/n	6	45	https://apps.des.qld.gov.au/env-authorities/pdf/eppr00874613.pdf
New Zealand	<14,000 l/day to land	n/n	20	n/n	n/n	25	n/n	n/n	30	https://www.orc.govt.nz/media/4459/form-6a-wastewater-discharge-to-land-from-domestic-system-updated-feb-2018.pdf
Moldova	General	125	25	n/n	n/n	15	n/n	2	35	http://lex.justice.md/index.php?action=view&vie

										w=doc&lang=1&id=329400
Mexico	Rivers	n/n	30	n/n	n/n	15	n/n	5	40	http://cepis.org.pe/mexican-official-standard-001ecol1996/
	Coastal	n/n	75	n/n	n/n	15	n/n	5	75	
Fiji	General	n/n	40	n/n	n/n	25	n/n	5	60	https://openjicareport.jica.go.jp/pdf/12355251.pdf
South Korea	<2000 m3/day	90	80	n/n	n/n	20	n/n	2	80	http://www.wepa-db.net/pdf/1003forum/12_korea_yangseok_cho.pdf
	>2000 m3/day	70	60	n/n	n/n	20	n/n	2	60	

4d. Carbon conversions (All sources are Ecoinvent v3.7 (cut-off) unless stated; Method: CML 2001 (superseded):climate change:GWP 100a).

Country	**Average kWh/m3**	**kgCO2e/kWh conversion factor**	**kgCO2e/m3**	**Source**
Italy	0.27	0.411581	0.112237	
Portugal	0.37	0.509904	0.188665	
Germany	0.43	0.537487	0.231119	
Finland	0.49	0.230592	0.11299	
Sweden	0.52	0.041462	0.021698	
Switzerland	0.57	0.102839	0.058618	
Spain	0.57	0.383463	0.21911	
Croatia	0.58	0.510709	0.296211	
Greece	0.58	0.741796	0.433553	
Norway	0.60	0.022947	0.01373	
UK	0.80	0.339658	0.272104	
Poland	0.89	1.02889	0.910567	
Netherlands	1.06	0.589151	0.623331	
Belgium	1.14	0.23474	0.267604	
Denmark	1.35	0.242799	0.327573	
Macedonia	0.34	1.01825	0.349175	
Serbia	0.66	1.085694	0.717697	
Bosnia	0.70	1.056708	0.737054	
Moldova	0.73	0.637195	0.464215	https://ecometrica.com/assets/Electricity-specific-emission-factors-for-grid-electricity.pdf
Kazakhstan	0.76	1.032328	0.785946	
Ukraine	0.79	0.568054	0.448132	
Russia	0.79	0.76938	0.610864	
Belarus	1.00	0.610874	0.608514	https://ecometrica.com/assets/Electricity-specific-emission-factors-for-grid-electricity.pdf
Canada	0.51	0.444057	0.228164	
United States	0.62	0.561612	0.34925	
Brazil	0.24	0.228308	0.054794	

Honduras	0.64	0.496141	0.31753	
Mexico	1.15	0.657385	0.755993	
India	0.24	1.458063	0.349935	
South Korea	0.243	0.688598	0.167329	
China	0.3	0.88582	0.265746	
Japan	0.53	0.663665	0.351742	
Singapore	0.56	0.460039	0.257622	
South Africa	0.2445	1.137141	0.278031	
Nigeria	0.58	0.571567	0.329603	
Fiji	0.31	0.4479	0.138849	Operating Marging in https://www.iges.or.jp/en/pub/list-grid-emission-factor/en?__cf_chl_jschl_tk__=5d6219bf677e24b98e043b6c7b561fcbd0f2f9f6-1612957688-0-AcSdi5lT8Yzv5Qwb-ziJDdF2kAniWMjv-aypSeovjDHhtLg_edssNOWtLU0_KdeKUSxnTQotsQCKSZ6SuvxEUsdPSBaYyPR_L-EdNMcDebbw_xEanRURnFpefah6CC14CJpB-0CsC-ijgJegjs9lSB6MzaV0JBZKBqUi4gbbiA7CR6Bh3j4cH7qxQ8J2lvWj9s-sTdQkicKAfv1kvJSEeuka6jzsXiQwnKbgMHv-GA-aO3Y9dWOeGGi8Fwq0tLH5jFuT73oZ9WyjpoE_F-AqaR7Eu41-DE_JJdQBAvPWkur0gHYIBS5Ij0WFfN1ORU_iXCczVtYcQB256fjSHZfDJ0MQPIwUIp_Fc6GeVGClyeIn
Palau	0.41	0.651	0.26691	https://iea.blob.core.windows.net/assets/eb3b2e8d-28e0-47fd-a8ba-160f7ed42bc3/CO2_Emissions_from_Fuel_Combustion_2019_Highlights.pdf
Fed. S of Micronesia	0.42	0.651	0.271793	https://iea.blob.core.windows.net/assets/eb3b2e8d-28e0-47fd-a8ba-160f7ed42bc3/CO2_Emissions_from_Fuel_Combustion_2019_Highlights.pdf
French Polynesia	0.65	0.651	0.424778	https://iea.blob.core.windows.net/assets/eb3b2e8d-28e0-47fd-a8ba-160f7ed42bc3/CO2_Emissions_from_Fuel_Combustion_2019_Highlights.pdf
Samoa	1.40	0.31	0.434	https://wedocs.unep.org/bitstream/handle/20.500.11822/10571/narrowing_emission_gap.pdf?sequence=1&isAllowed=y
New Zealand	0.61	0.118773	0.072011	
Australia	0.71	0.973686	0.689914	