Transitioning to Low-Carbon Drinking Water and Sanitation Services: An Assessment of Emission and Real Water Losses Efficiency of Water Utilities

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1. Introduction

Environmental efficiency is considered as a foundational component of sustainable development (Matsumoto et al. 2020). Efforts to reduce greenhouse gas emissions (GHGs) to tackle climate change have put a spotlight on the environmental efficiency of water utility and sanitation services. They also urge these operations to transition into low-carbon operations. A substantial energy input is used in providing drinking water and sanitation services, particularly water supply augmentation, water and sewage treatment and pumping. In many countries, the traditional water supplies have been under pressure due to increased drought conditions and climate variability raising water security concerns. Climate-independent water supply options such as desalinisation have exacerbated energy use in recent times.

The drinking water and sanitation sector encompasses several Sustainable Development Goals (SDGs) of the United Nations. SDG #6 aims at achieving clean water and sanitation throughout the world; SDG #13 aims at implementing climate action and to reduce global greenhouse gas emissions. The water sector is also pivotal in ensuring SDG #12, sustainable consumption and production aiming at reducing the consumption of natural resources and pollution.

Environmental efficiency of drinking water and sanitation water services has received increased attention throughout the world in recent times (Ananda and Hampf 2015; Molinos-Senante et al. 2014; Molinos-Senante et al. 2018b; Ananda 2018, 2019; The Water Research Foundation 2019). This is unsurprising given the critical and multi-faceted roles that the sector plays in achieving sustainable development. In fact, the water–energy nexus has been a thriving area of publication in recent times, Pacetti et al. (2015), Chen and Chen (2016), Ackerman and Fisher (2013) and Head and Cammerman (2010).

The increased policy action to mitigate climate change and greenhouse emissions in recent times has forced the utilities sector to increase its environmental efficiency.

The GHG footprint of the water and sanitation sector is not insignificant. Globally, the water sector's GHG contribution is equivalent to 20% of the sum of committed reductions by all countries in the Paris Agreement (Ballard et al. 2018). In 2018, the electricity, gas, water and sanitation sector recorded 189.8 Mt CO_2-e and contributed 35.3% of Australia's total emissions (Commonwealth of Australia 2020). It should be noted, however, that the overwhelming majority of emissions in this figure come from the electricity and gas sector. Most reported water sector GHG emissions are energy-related, and they exclude emissions from non-energy related sources, often referred to as 'fugitive emissions' such as methane and nitrous oxide from wastewater treatment.

The drinking water utilities sector plays a critical role in sustaining communities and supporting economic growth. Figure 1 summarizes the global and local challenges faced by water utilities. It highlights the transformations that are occurring at three different levels: at the global level, national level and at the water utility level. At the global level, commitments made to international climate change agreements such as the Paris Agreement urge the signatory countries to reduce greenhouse gas emissions in an effort to limit the global temperature increase. For example, Australia is committed to reduce its 2000 emission levels by 5% by 2020 and 26% below 2005 levels by 2030 (Australian Government 2020). Several Australian states have a net zero emissions target by 2050. Moreover, increasing urbanization and population growth have put upward pressures on greenhouse gas emissions. At sectoral levels, various industries have come up with national plans to address greenhouse gas emissions and mitigate adverse climate change impacts. For example, the water industry peak body in Australia has developed a cost-effective and risk-based tool to assess carbon abatement for water utilities (Water Services Association of Australia 2012).

The majority of the sector's energy needs are met by fossil fuel electricity (Ananda 2018). The increased reliance on climate-independent water supply sources such as desalinization and recycled water has exacerbated the fossil fuel energy use and greenhouse gas emissions. The use of desalination water has increased significantly following the Millennium drought in Australia. Significant capital investment has been made on constructing desalination plants and enhancing water recycling capacity across the country in order to address water security concerns. All these new climate-independent capital assets are energy-intensive. Transforming the energy mix to renewables through innovative technologies and building resilience of water utilities to face adverse impacts of climate change while delivering 'value for money' for customers are the core challenges faced by water utilities. Transformation of the energy mix to renewable sources will enable to establish a sector low-carbon and sanitation services. This transformation should be aided by appropriate measurement frameworks to benchmark environmental efficiency.

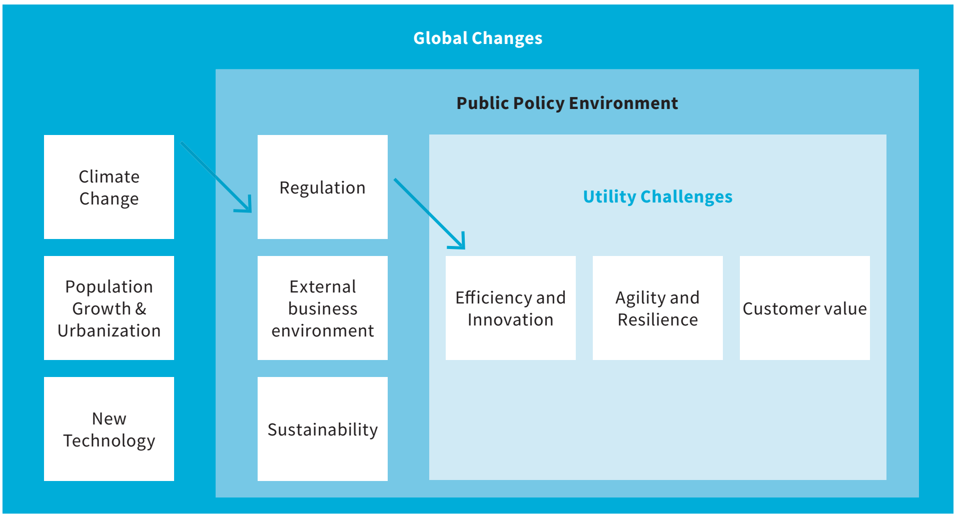

Figure 1. Framework used to respond to global and local challenges.

To formulate effective economic policies that align with sustainability, research that measures the relationship between emissions and economic growth is vital (Oh 2010b). Micro-level studies are needed to understand the links between the energy footprint and its economic and environmental performance. Some of the pertinent research questions include how to internalize undesirable outputs of production, what are the drivers of energy efficiency, how operational processes influence the energy footprint and thereby the economic performance, and what regulatory changes are required to promote sustainable development?

Utility regulation has traditionally been dominated by a neo-classical economic paradigm that seeks to control the natural monopoly power of utilities such as water, electricity and telecommunications. Often, conventional regulation is based on partial indicators or statistical benchmarking. However, the focus has been on desirable outputs and more recently quality aspects of outputs. In Europe, recently, there have been efforts to improve the knowledge base in urban water management from a resource efficiency perspective (European Environmental Agency 2014). Several recent studies focused on energy productivity and emissions (Ball et al. 2015; Hampf 2014; Dubrocard and Prombo 2012; Zhang et al. 2011; Choi et al. 2015). As regulated authorities, water utilities must select climate change responses that are cost-effective and environmentally efficient. By including bad outputs such as GHG emissions in the productivity analysis, policy makers could send a signal to water utilities to achieve emission reductions through energy efficiency, demand management, waste heat capture, energy capture and switching to renewables and other alternative energy sources (Water Services Association of Australia 2012). Such assessments will invariably facilitate the sector to transition into an environmentally efficient, low-carbon sector.

Although a large body of literature exists regarding the conventional productivity assessment in the drinking water and sanitation sector (Lannier and Porcher 2014; Molinos-Senante et al. 2018a; Molinos-Senante et al. 2017; Ananda 2013; Cunningham 2013; Sala-Garrido et al. 2019), studies that integrate environmentally undesirable outputs into productivity assessments are relatively scarce (Ananda and Hampf 2015; Molinos-Senante et al. 2014). It is noteworthy that efforts have been made in this regard in developing countries as well. For example, Kamarudin and Ismail (2016) incorporated non-revenue water as a bad output into the water utility performance in Malaysia. Kumar (2010) emphasized that the performance benchmarking of Indian water utilities must take into account service delivery aspects and non-revenue water. We extend the above strand of research by developing an environmentally sensitive productivity approach to benchmark water utilities. Our approach can accommodate multiple undesirable outputs of production. This study extends the work of Ananda and Hampf (2015) by applying environmentally adjusted productivity modelling framework to the Australian drinking water and sanitation services sector from 2013/14 to 2018/19. The specific objectives of this research are:

- To account for greenhouse emissions and real water losses in drinking water and sanitation services;
- To compute an environmentally sensitive productivity growth index;
- To analyze the drivers of productivity trends in the drinking water and sewage sector.

The remainder of this chapter is organized as follows. The next section outlines some theoretical underpinnings of the measurement of efficiency and productivity whilst accounting for undesirable outputs such as greenhouse emissions. It also discusses the data and the model specification used for the analysis. Section 3 discusses the main findings of the empirical analysis and the final section concludes the chapter.

2. Methods

Benchmarking productivity has been widely used in economic regulation of utility industries. A wide variety of water utility benchmarking approaches have been used in the literature, ranging from partial indicators of productivity to sophisticated statistical modeling approaches (Berg and Marques 2011; Torres and Paul 2006; Romano and Guerrini 2011; Cunningham 2013). They include total factor productivity, stochastic frontier analysis and data envelopment analysis (DEA). These methods are often used for quantitative assessments of the economic performance of industries, firms or countries. The nonparametric approach of DEA has several advantages over parametric methods, including the fact that it does not require a priori assumptions over the functional relationship that underpins the production process. This advantage comes at the cost of statistical noise that may be introduced into the analysis (Kneip et al. 2008; Simar and Wilson 2000).

DEA specifications take the form of a multi-factor productivity model that compares inputs and outputs of a production process. By using linear programming techniques, the approach constructs a non-parametric efficiency frontier comprising best-performing firms or benchmark firms. An individual firm's performance can be measured by comparing it to the efficiency frontier constructed.

Traditional measures of productivity growth such as Malmquist, Törnquist and Fischer indices focus only on the production of desirable outputs and do not consider undesirable outputs such as GHGs. The Malmquist index is based on ratios of distance functions and can be decomposed into efficiency change and technical change components. However, the production of desirable outputs, in this case drinking water and sanitation services, invariably involves environmental pollution, greenhouse gas emissions and water losses, which can be collectively termed undesirable outputs. Chung et al. (1997) highlighted that ignoring undesirable outputs of production from productivity measurement will lead to biased results undermining sustainability. In particular, the consideration of pollution externalities is important in benchmarking and regulatory decision making.

Chung et al. (1997) developed the Malmquist–Luenberger (ML) index that extends the conventional Malmquist productivity analysis to include undesirable outputs to produce a more meaningful measure of industrial performance (Shen et al. 2019). Based on the work by Pastor and Lovell (2005), Oh (2010a) developed the Global Malmquist–Luenberger (GML) index approach which circumvented the infeasibility problem of ML linear programming specifications. This study uses the GML index to estimate an environmentally adjusted productivity index. The global ML index can be decomposed into efficiency change and technical change.

The global ML index extends the analysis by measuring the shift in the frontiers between two periods (the technical change component) by comparing their relative position to the global frontier. This global frontier is the closure of the technology constructed by the total sample of all entities and their input–output combinations for all periods. This study applies the GML index using an input-oriented DEA. Appendix A provides the technical details of DEA, the global ML productivity index and its decompositions.

Data and Model Specification

Our data focus on a sample of integrated water and sanitation utilities in Australia. A dataset was collated for the period 2013–14 to 2018–19 from the National Performance Report 2018–19 (Bureau of Meteorology 2020). The dataset covered a total of 84 water utilities. It should be noted that utilities serving less than 10,000 customers are not part of the national reporting framework. We only selected the integrated water and sewerage utilities.[1] Utilities providing bulk water,[2] drinking water only and sewerage only were removed (9 utilities) from the original dataset. Fifteen utilities were removed from the sample due to missing data. The final sample comprised of 360 observations of 60 water and sanitation utilities over a 6-year period (2014–2019). The sample utilities come from all states of Australia except Tasmania. The sample water utilities included in the study provided both drinking water and sewerage services to a population of 21.5 million (approximately 86% of the total population) in 2018/19.

The model specification is a crucial step in production frontier studies. Therefore, our choice of input and output variables is driven by the literature and the empirical context. Many past studies on productivity performance have used operations and maintenance expenditure and capital expenditure as inputs for water sector productivity assessments and some studies have used the length of the water delivery network when reliable capital costs are not available (Worthington and Higgs 2014; Saal et al. 2007; Saal and Reid 2004; Ananda 2013). Accordingly, this study uses the operating cost (adjusted for inflation) and the length of water mains delivery network as a proxy for the capital stock as inputs in the DEA model formulation.

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1 The terms 'water utilities' and 'water and sanitation utilities' are used interchangeably in this chapter. Most Australian water utilities provide an integrated service of potable for water drinking and sanitation purposes and collect wastewater from premises.

2 Bulk water utilities are the wholesale water sellers that supply raw water to retail water utilities, and they do not directly deal with water and sanitation customers.

The operating cost of Australian water utilities include water resource access charges, purchase and transfer of raw water, salaries, wages and overheads of staff, and materials, chemicals and energy costs. The length of water mains included the network length that covers the transfer, distribution and reticulation mains.

The most widely used output measures of the water industry include the volume of drinking water supplied,[3] the volume of sewage collected and the number of connected properties (Ananda and Pawsey 2019; Saal et al. 2007). We chose the core outputs of the volume of drinking water delivered and the volume of sewage collected as good outputs and net greenhouse gas emissions and real water losses as bad outputs. The net greenhouse gas emissions variable measures the environmental footprint water and sanitation services and other activities. There is a tradeoff between emissions footprint and certain activities such as increased sewage treatment, which entails water quality benefits at the expense of increased emissions. The variable measures the direct (Scope 1) and indirect (Scope 2) emissions in tons of carbon dioxide equivalent. The values are adjusted for any carbon sequestration activities carried out by the water utility using the National Greenhouse Accounts (NGA) conversion factors. In addition to greenhouse gas emissions, we included real water losses as an undesirable output. Real water losses in the potable distribution system are due to leakage and overflows from mains, service reservoirs and service connections prior to customer meters (National Water Commission 2014).

Drinking water and sanitation providers have limited influence on the amounts of outputs produced because the government regulation mandates them to deliver potable water and sanitation services to the assigned population within a geographical area. Hence, we assume that a typical water utility minimizes inputs to a given set of good outputs and bad outputs. Accordingly, we specified the DEA linear programming model as an input minimization model.

3. Results

3.1. Descriptive Statistics and Emission Trends

Descriptive statistics of the input and output variables included in the analysis are presented in Table 1. Variables have been converted to per property values, which partially account for the sample heterogeneity in water and sanitation utilities.

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3 The term 'drinking water' is used for brevity but it also includes water uses for sanitation.

The scatterplot matrices of input and output variables are shown in Figure 2. Pearson correlation coefficients are shown above the diagonal. Figure 2 indicates that there are no strong correlations among the frontier variables. There was a weak positive correlation between real water losses and the average residential water delivered. The same was true for greenhouse gas emissions and average residential water delivered.

Table 1. Descriptive statistics of variables.

Variable	Mean	S.D.	Max.	Min.
Bad Outputs				
Greenhouse emissions (tons/1000 properties)	396.1	205.1	1220.0	25.6
Real water losses (L/connection/day)	2.9	1.9	17.8	0.0
Good Outputs				
Residential water delivered (ML/property)	204.4	78.6	518.5	77.2
Wastewater collected (ML/property)	220.9	64.4	480.3	68.9
Inputs				
Length of water mains (km)	2798.6	4949.7	27,463.0	234.0
Combined operational cost ($/property)	979.5	292.3	3840.0	474.3

The temporal trends of the greenhouse gas emissions modelling are shown in Figure 3. Figure 3 shows that greenhouse emissions in the water sector vary with the utility size category. The National Performance Framework classifies water utilities into four categories based on the number of customers: Major = >100,000 customers (13 utilities); Large = 50,000–100,000 customers (10 utilities); Medium = 20,000–50,000 customers (17 utilities); and Small = 10,000–20,000 customers (20 utilities). The Major utility category recorded the lowest level of emissions per 1000 properties while the Medium utilities recorded the highest emissions levels. A range of factors affects GHGs of water utilities including the level of raw water treatment needed, the level of water demand, the degree to which the water utility relies on desalination and water recycling, the topography of the region, and the extent of the water pumping and wastewater network. Smaller utilities have higher energy use and emissions as they are typically located in regional and rural areas where water pumping must be carried out over large distances and the population is sparsely distributed. The GHG emissions of Major and Large utility categories have declined over recent times. The median GHG emissions have increased for all utility categories except the Medium category in 2018/19. One contributory factor could be the policies to reduce emissions culminating to the implementation of carbon tax in 2012. Although the carbon tax legislation in Australia was subsequently repealed in 2014, the GHG emissions of the water utilities appear to decline.

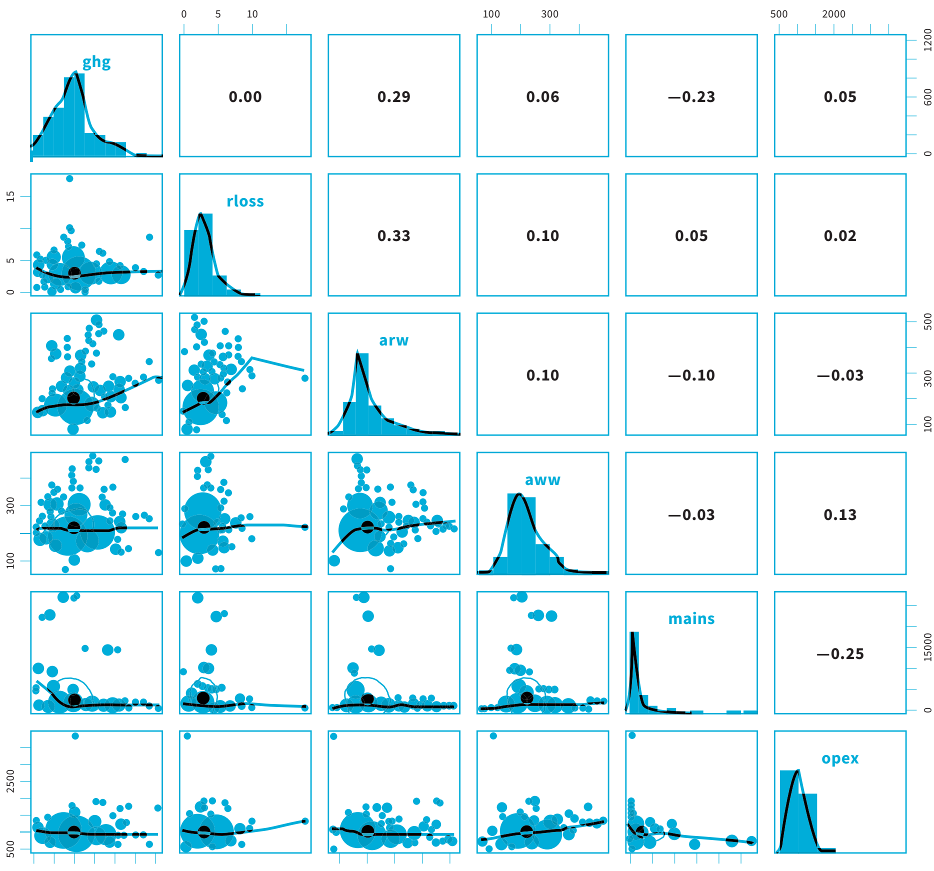

Figure 2. Scatterplot matrix of input and output variables. Key: ghg = Greenhouse gas emissions; rloss = Real water losses; arw = Average residential water supplied; aww = Average wastewater collected; mains = The length of water mains; opex = operational expenditure.

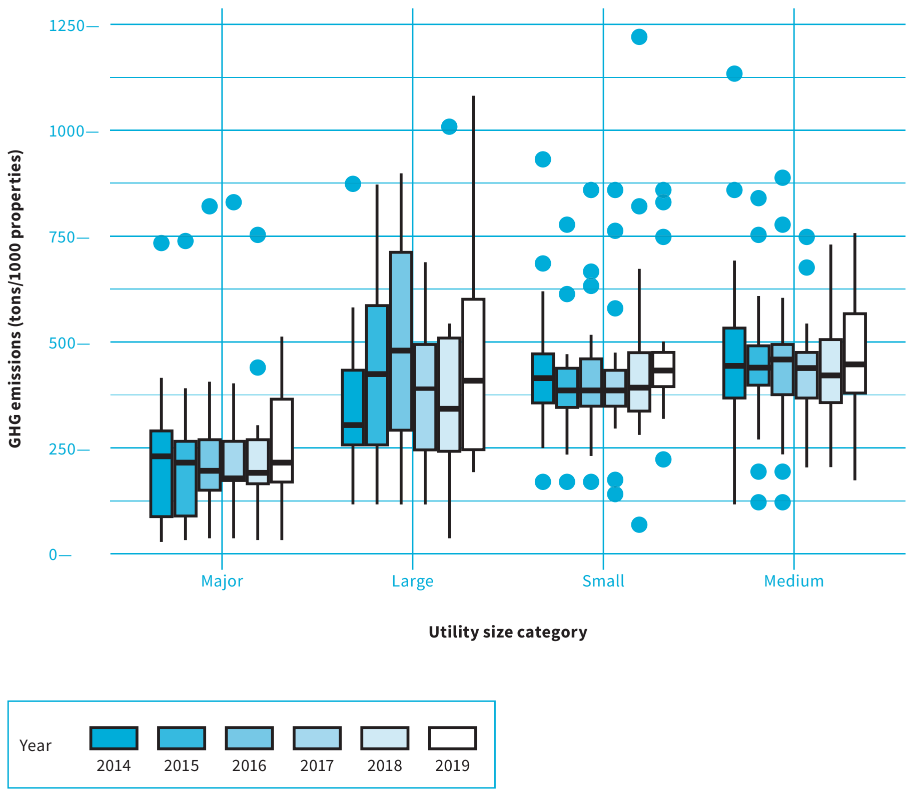

Figure 3. Boxplot of GHG emission trends by utility size category.

3.2. Productivity Trends without Undesirable Outputs

This section discusses the productivity trends. Table 2 presents the results of the conventional productivity analysis using the global Malmquist productivity index, which disregards the undesirable outputs (greenhouse gas emissions and water losses) in the estimation. Productivity change values greater (less) than one indicate an increase (decrease) in the productivity. Similarly, the values greater (less) than one in efficiency change (EC) and technical change (TC) indicate progress (regress) with regard to the components.

Table 2 summarises the mean cumulative productivity growth results. It indicates that conventional productivity of the water sector ranged from 3.4% (2018/19) to 7.7% (2016/17) during the study period. The productivity growth peaked during 2014/15 and 2016/17. A productivity growth of over 7% was recorded for both abovementioned periods. On average, the productivity has increased approximately by 5% per annum over the study period. However, since 2016/17, the productivity growth has somewhat declined.

Table 2. The conventional productivity, efficiency change and technical change from 2014/15 to 2018/19.

Year	PC [1]	EC [2]	TC [3]
2014/15	1.0741	1.0965	0.9797
2015/16	1.0394	1.0584	0.9828
2016/17	1.0772	1.0856	0.9930
2017/18	1.0478	1.0639	0.9859
2018/19	1.0340	1.0667	0.9703

[1] Productivity Change; [2] Efficiency Change; [3] Technical Change.

3.3. Productivity Trends with Undesirable Outputs

Table 3 and Figure 4 present the average environmentally adjusted cumulative productivity results using the global Malmquist–Luenberger productivity index. This productivity index accounted for greenhouse gas emissions and real water losses that occur in the production process. The environmentally adjusted productivity growth has occurred throughout the study period, but it is on a declining trajectory. The productivity growth ranged from 2% (2018/19) to 4.4% (2014/15) during the study period. Overall, the productivity has improved by 3% per annum on average. Over 4% productivity growth was recorded during 2014/15 and 2015/16. As shown in Figure 4, the efficiency change and productivity change growth followed a similar trajectory and efficiency change was largely responsible for the improved productivity outcome during the study period.

Figure 5 compares the conventional productivity growth as measured in the global Malmquist index and the environmentally adjusted productivity growth as measured in the global Malmquist–Luenberger index. In all time periods analyzed, except 2015/16, the conventional productivity growth outstripped the environmentally adjusted productivity growth during the study period.

Table 3. The environmentally adjusted productivity, efficiency change and technical change from 2014/15 to 2018/19.

Year	PC [1]	EC [2]	TC [3]
2014/15	1.0436	1.0387	1.0091
2015/16	1.0429	1.0732	0.9803
2016/17	1.0333	1.0536	0.9880
2017/18	1.0245	1.0296	1.0000
2018/19	1.0204	1.0393	0.9859

[1] Productivity Change; [2] Efficiency Change; [3] Technical Change.

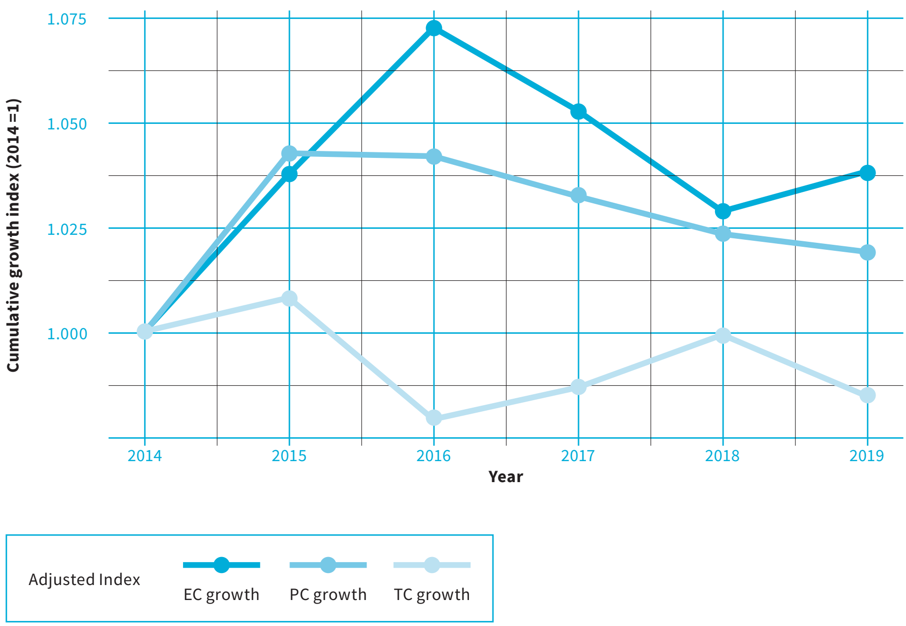

Figure 4. Environmentally adjusted cumulative productivity growth and its decompositions for the Australian drinking water sector, 2014 to 2019. Key: EC = Efficiency Change; PC = Productivity Change; TC = Technical Change.

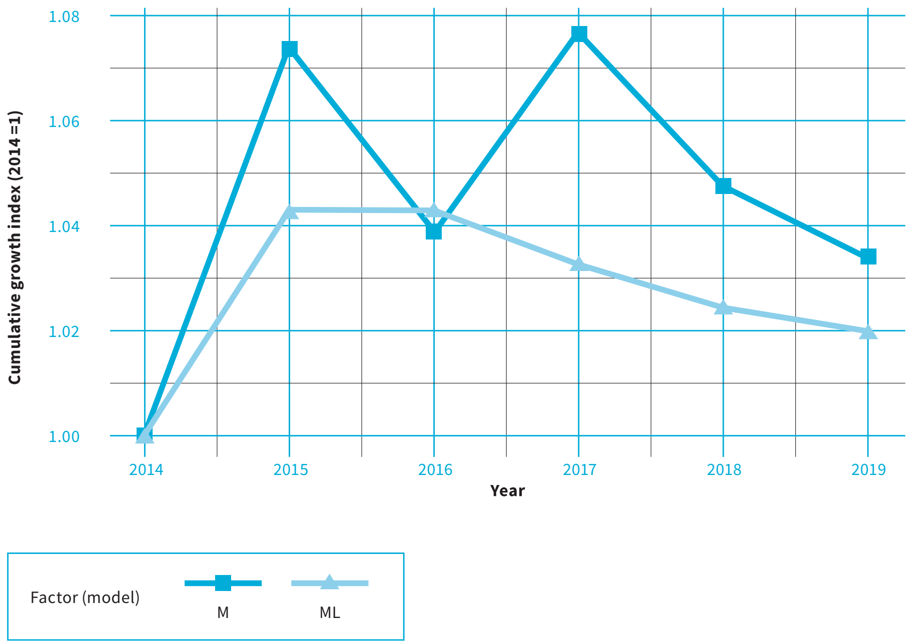

Figure 5. Comparison of environmentally adjusted cumulative (ML) and conventional (M) productivity trends for the Australian drinking water sector from 2014 to 2019. Key: M = Malmquist index; ML = Malmquist–Luenberger index.

3.4. Efficiency Change Trends

It would be useful to understand the underlying drivers of this productivity result. This can be explored by examining the decomposition of the productivity change index: the efficiency change and technical change. As can be seen from column 3 of Table 2, the traditional productivity improvement can be attributed to the efficiency change. The largest efficiency change growth (7%) occurred in 2015/16. The growth in efficiency change outstripped the technical regress facilitating an overall productivity growth.

Both conventional and environmentally adjusted efficiency change indices recorded growth during the study period. In fact, the productivity outcomes were largely, if not entirely, driven by the growth in the efficiency change. The conventional average annual growth of efficiency change ranged from 5.8% to 9.6% (Table 2). The environmentally adjusted efficiency change growth ranged from 3% to 7.3% over the study period. These results suggest that the average water utility experienced a 'catching up' effect moving closer to the contemporaneous technology frontier over the study period. In terms of environmentally adjusted index, water utilities recorded the highest catching up performance during the 2015–2017 period.

3.5. Technical Change Trends

Column 4 of Table 2 suggests that the technical regress occurred across all time periods except 2014/15 and 2017/18 under the conventional index framework. Approximately 2% annual average technical regression occurred during the study period. This indicates that the contemporaneous frontier has shifted inwardly. Interestingly, environmentally adjusted index framework yielded a slightly better technical change result with 0.91% technical progress in 2014/15 and neutral technical change (0%) in 2017/18 while showing technical regression the rest of the time (Table 3). The growth in efficiency change has clearly outstripped the growth in technical change. The growth trend of productivity change has followed a similar trajectory to that of efficiency change.

An increase in efficiency change coincides with the initial phase of the regulatory cycle (2014–2018) but this analysis cannot reason this as causation because many confounding factors are at play here. The technical regress during 2014/15 to 2017/18 means that water utilities did not adopt innovative technologies to minimize costs during this period. One plausible reason for this technical regression is that an increased technical regulation requirement preventing a best practice firm from using more inputs to produce a given set of outputs. These regulatory requirements include increased standards of security of water supply and environmental compliance requirements (Cunningham 2013). A 'knock-on' effect due to significant capital investments made in the aftermath of the Millennium drought in Australia to ensure water security may have also contributed to the technical regress. Such a level of capital investments cannot be sustained for a long time, but it appears that the sector's innovation efforts need lifting. It is also hard to pinpoint a single reason for the fluctuation of environmentally adjusted technical change without more in-depth research.

3.6. Productivity Trends by State and Utility Size Category

Variation in productivity and its decompositions were analyzed next. Utilities were classified into four size categories (see Section Data and Model Specification) and the trends were examined by state. Australia has eight states and territories and our dataset contained water utilities located in all states except Tasmania. Water and sanitation utilities in New South Wales were divided into two sub-categories, distinguishing between the metropolitan (NSW-m) and country or regional (NSW-c) water utilities. Figure 6 shows the environmentally adjusted productivity trends by state and utility category. It indicates that the productivity trends among states and utility categories are not homogenous. For example, Victorian Small water utilities recorded the largest environmentally sensitive productivity improvement over the study period while the productivity performance of NSW-country water utilities deteriorated somewhat.

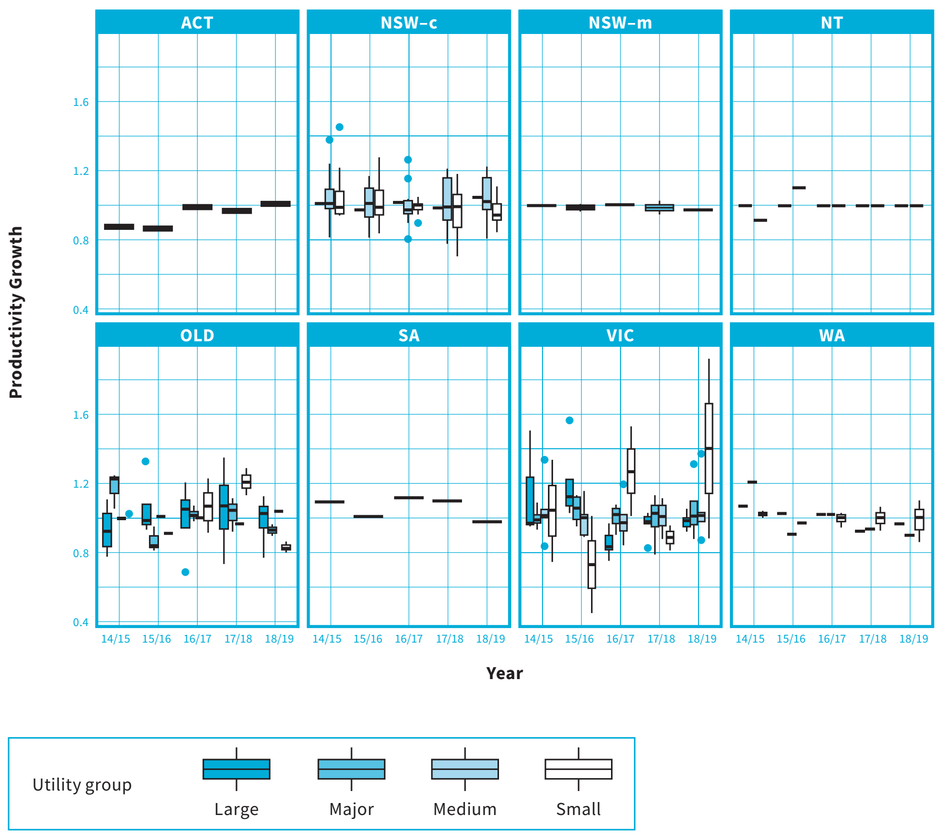

Figure 6. Environmentally sensitive productivity growth trends by state and utility group. Key: ACT = Australian Capital Territory; NSW-c = New South Wales—country; NSW-m = New South Wales—Metropolitan; NT = Northern Territory; QLD = Queensland; SA = South Australia; VIC = Victoria; WA = Western Australia.

The environmentally adjusted productivity trends in Australian Capital Territory (ACT), New South Wales metropolitan (NSW-m) and Northern Territory (NT) have been stagnant since 2016. The Victorian water utilities recorded the greatest variation in environmentally sensitive productivity results while NSW-m recorded the least variation in productivity over the study period. Water utilities in Queensland (QLD), South Australia (SA) and Western Australia (WA) showed a decline in environmentally sensitive productivity over the study period. In terms of utility size category analysis, Figure 6 shows that the performance of Major utilities in Queensland has deteriorated markedly since 2017/18.

4. Discussion and Conclusions

Undesirable and environmentally harmful outputs of production are often ignored by the traditional measures of productivity. It is worthwhile to note the discrepancy in the conventional productivity results and environmentally adjusted productivity results. Particularly, the conventional productivity analysis yielded a higher productivity growth compared to the environmentally adjusted productivity index. This result is consistent with the findings of similar studies (Oh 2010a; Ananda and Hampf 2015). The main implication of this result is that using conventional productivity frameworks will over-estimate the real productivity growth in the sector. The discrepancy in productivity results from the two approaches is not insignificant.

The overestimation of productivity is problematic for the sector for several reasons. First, the current productivity assessment totally ignores bad outputs such as GHG emissions, which contribute to climate change. In other words, water utilities with high emissions and causing environmental damage could be incorrectly deemed as 'best performers' or industry benchmarks. Second, from a policy evaluation perspective, the performance of water utilities that heavily rely on energy-intensive water supplies may differ from utilities that rely on environmentally friendly and less energy-intensive raw water sources. For example, water abstracted from a protected catchment or closed storage catchment is usually higher quality than water from open storage catchment and requires less treatment and therefore fewer emissions. Third, water utilities that have a lower environmental footprint may be penalized in traditional productivity evaluations. Fourth, by not accounting for real water losses and emissions therein, water utilities may appear 'productive' from an economic point of view at the cost of environment, which is detrimental to achieving SDG #12—sustainable production aiming at reducing pollution.

Within the framework of the global Malmquist–Luenberger DEA, this chapter presented an approach to measure dynamic changes in environmentally adjusted productivity of drinking water and sanitation services in Australia. The results indicated that in the sample period evaluated, the water and sanitation sector had an annual average growth rate of 3%. This productivity growth came from the growth in efficiency change. The analysis also revealed a declining 'green' (environmentally adjusted) productivity growth trajectory. Several factors such as increasing energy costs in recent times may have contributed to this decline in productivity. Steps must be taken to explore reasons for this trend and to minimize greenhouse gas emissions and real water losses using least cost strategies.

One limitation of the present study is that it assumed that the institutional environments in which the water utilities operate are homogenous. Additionally, the influence of extreme values on the production frontier is ignored. Future research should focus on addressing these two limitations. Particularly, accounting for group heterogeneities manifested by the geographical distribution of water utilities and varied jurisdictional policy frameworks are important in developing robust productivity assessments for sustainable development. Another improvement to the present study is to compute bias-corrected productivity estimates using bootstrap methods proposed by Simar and Wilson (1998). Uncorrected efficiency estimates tend to be slightly upwardly biased, although the overall distribution of estimates remains the same.

The approach presented in this chapter integrated the ideals of sustainability into the drinking water and sanitation services delivery by including greenhouse gas emissions and real water losses. Being a crucial sector, which deals with several SDG arenas, it is important to develop and test assessment frameworks that foster SDG targets. Without robust sustainability measurement frameworks, it is difficult not only to track the sectoral progress but also to transform water production and sanitation service delivery systems into more sustainable ones. Embedding innovative assessment frameworks such as the one presented in this chapter with regulatory frameworks will expedite the transition to low carbon drinking water and sanitation provision while advancing the SDGs.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

With input-oriented DEA, the linear programming model is configured in a manner that maximizes the technical efficiency of the *i*-th decision-making unit (DMU), in order to achieve a given output level. Following the notation of Coelli et al. (1998), this can be solved as an input minimization problem using the following LP programme.

$$\begin{aligned} &\min_{\theta,\lambda}\theta, \\ &s.t. \\ -\boldsymbol{y}_i+\boldsymbol{Y}\lambda &\geq 0, \\ \theta\boldsymbol{x}_i - \boldsymbol{X}\lambda &\geq 0, \\ \lambda &\geq 0, \end{aligned} \tag{A1}$$

where $\boldsymbol{y}_i$ is an $M \times 1$ vector of outputs produced by the i-th DMU, $\boldsymbol{x}_i$ a $K \times 1$ vector of inputs used by the i-th DMU, $\boldsymbol{Y}$ is the $M \times N$ matrix of outputs of N DMUs in the sample, $\boldsymbol{X}$ is the $K \times N$ matrix of inputs of the N DMUs, λ is an $N \times 1$ vector of weights and θ is a scalar measure of technical efficiency which takes a value between 0 and 1 inclusive.

The above formulation is known as the constant returns to scale (CRS) DEA formulation and it can be modified to allow the Variable Returns to Scale (VRS) DEA technology by adding a convexity constraint to the original minimization problem, resulting in the following linear program:

$$\begin{aligned} &\min_{\theta,\lambda}\theta, \\ &s.t. \\ -\boldsymbol{y}_i+\boldsymbol{Y}\lambda &\geq 0, \\ \theta\boldsymbol{x}_i - \boldsymbol{X}\lambda &\geq 0, \\ \boldsymbol{N1}'\lambda &= 1, \\ \lambda &\geq 0, \end{aligned} \tag{A2}$$

where $\boldsymbol{N1}$ is a vector of ones. The VRS formulation of DEA produces 'pure' technical efficiency devoid of scale effects and efficiency scores are either greater than or equal to those from the CRS problem. A scale efficiency measure for each DMU can be obtained by conducting both a CRS and a VRS DEA and then decomposing the DEA scores obtained from the CRS DEA into two components: one due to scale inefficiency and the other due to 'pure' technical inefficiency. The analysis assumed CRS technology following Färe and Grosskopf (2003). It should be also noted that the Australian water and sanitation sector is a mature industry and the above assumption is not unreasonable.

Calculating the Malmquist Productivity Index

Following the framework set down by Caves et al. (1982), the input-oriented Malmquist productivity change index is:

$$M_i^{t+1}\left(y_{i,t},\ x_{i,t},\ yi,\ _{t+1},\ x_{i,t+1}\right) = \left[\frac{D_I^t\left(y_{i,t+1},\ x_{i,t+1}\right)}{D_i^t\left(y_{i,t},\ x_{i,t}\right)} \times \frac{D_i^{t+1}\left(y_{i,t+1},\ x_{i,t+1}\right)}{D_i^{t+1}\left(y_{i,t}, x_{i,t}\right)}\right]^{1/2} \tag{A3}$$

where subscript i denotes the DMU (urban water authority in this case), M is the productivity of the most recent production point $\left(x_{i,t+1}, y_{i,t+1}\right)$ (for DMU i, using period t + 1 technology) relative to the earlier production point $\left(x_{i,t}, y_{i,t}\right)$ (for DMU i, using period t technology), y refers to outputs and x refers to inputs. Input distance functions are denoted as D. With regard to input-orientation, productivity values greater (less) than one indicate positive (negative) TFP growth from period t to period t + 1. In order to delineate the sources of TFP growth, Equation (A3) can be re-written as follows:

$$\begin{aligned} & M_i^{t+1}\left(y_{i,t},\ x_{i,t},\ y_{i,t+1},\ x_{i,t+1}\right) \\ & = \frac{D_i^{t+1}\left(y_{i,\ t+1}, x_{i,t+1}\right)}{D_i^t\left(y_{i,t}, x_{i,t}\right)}\left[\frac{D_i^t\left(y_{i,t+1},\ x_{i,t+1}\right)}{D_i^{t+1}\left(y_{i,t+1},\ x_{i,t+1}\right)} \times \frac{D_i^t\left(y_{i,t},\ x_{i,t}\right)}{D_i^{t+1}\left(y_{i,t}, x_{i,t}\right)}\right]^{1/2} \\ & = EC_i^{t,t+1} TC_i^{t,t+1} \end{aligned} \tag{A4}$$

where M, the Malmquist total factor productivity, is the product of technical efficiency change ($EC^{t,\ t+1}$) and technological change ($TC^{t,\ t+1}$). The global ML index can be decomposed as

$$\mathrm{GML}^{t,\ t+1} = \underbrace{\frac{\theta^{t+1}\left(\boldsymbol{x}_{t+1}, \boldsymbol{y}_{t+1}, \boldsymbol{u}_{t+1}\right)}{\theta^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t, \boldsymbol{u}_t\right)}}_{\mathrm{MLEff}^{t,\ t+1}} \cdot \underbrace{\sqrt{\frac{\theta^t\left(\boldsymbol{x}_t, \boldsymbol{y}_t, \boldsymbol{u}_t\right)}{\theta^G\left(\boldsymbol{x}_t, \boldsymbol{y}_t, \boldsymbol{u}_t\right)} \cdot \frac{\theta^G\left(\boldsymbol{x}_{t+1}, \boldsymbol{y}_{t+1}, \boldsymbol{u}_{t+1}\right)}{\theta^{t+1}\left(\boldsymbol{x}_{t+1}, \boldsymbol{y}_{t+1}, \boldsymbol{u}_{t+1}\right)}}}_{\mathrm{GMLTech}^{t,\ t+1}} \tag{A5}$$

where the superscript "G" denotes the global frontier. Again, the global Malmquist index can be obtained by removing the constraint on the bad outputs when calculating the distance functions.

Several scholars have proposed to modify the conventional productivity indices such as the Malmquist index to account for bad outputs (Yörük and Zaim 2005; Färe et al. 2012; Oh and Lee 2010; Zhang et al. 2011; Zhou et al. 2010). The seminal work of Chung et al. (1997) stands out in accommodating undesirable outputs in the productivity measurement. They modified the conventional Malmquist index by Caves et al. (1982) and developed the Malmquist–Luenberger index, which can explicitly take bad outputs into account. One limitation of the Malmquist–Luenberger index is the possible infeasible solutions when undesirable outputs are included in the estimation (Färe et al. 2001).

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