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Production and scale efficiency of South African water utilities: the case of water boards

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ABSTRACT

South Africa is a water scarce country with deteriorating water resources. Faced with tight fiscal and water resource constraints, water utilities would have to adopt technically efficient water management technologies to meet developmental socio-economic objectives of universal coverage, aligned to the United Nation's Sustainable Development Goal 6. It is important to measure the technical efficiency of utilities as accurately as possible in order to inform policy. We do this by using a non-parametric method known as Data Envelopment Analysis to determine, measure, analyse and benchmark the technical efficiency of all water boards in South Africa. Our contribution to the literature is twofold: This is the first paper to model technical efficiency of water boards as utility suppliers and guardians of water services in South Africa, and second, we address the over- and underestimation issues of technical efficiency measurement in the water sector. We do this by modelling one of the most pronounced negative externalities from water provision (water losses) as an undesirable output using the approach developed by You and Yan. We find, on average, technical efficiency of water boards is 49%, with only three of the nine water boards technically efficient. Six of the smaller water boards showed high levels of inefficiency with an inefficiency rate of 51%, which is equivalent to wastage in expenditure of R3.7 billion. Six water boards operate at increasing returns to scale and two are scale efficient. Only Rand and Sedibeng water boards exhibited decreasing returns to scale. Therefore, redirecting potential efficiency savings to optimal uses could result in technical and scale efficiency for the sector. Scale efficiency results seem to support larger regional water boards as small- to medium-sized water boards are scale inefficient with low technical efficiency. For example, Amatola Water (small water board) with an efficiency score of only 16% has a total expenditure of 18% of that of Umgeni (large water board), but sells only 6.7% of the quantity sold by Umgeni. Amatola also has seven times the proportion of water losses compared with Umgeni and charges 1.6 times the tariff of Umgeni. The ratio model with an undesirable output outperforms previous methods to deal with undesirable (bad) outputs, which either provide an over- or underestimation of technical efficiency.

Key words: Data Envelopment Analysis, Scale efficiency, Technical efficiency, Water boards, Water losses

HIGHLIGHTS

- Maiden paper is to benchmark technical efficiency of all water boards in South Africa.
- We address the over- and underestimation issues of technical efficiency measurement in the water sector by treating undesirable output.

1. INTRODUCTION

The United Nations 2030 Agenda for Sustainable Development was adopted in September 2015. It established 17 Sustainable Development Goals (SDGs) relating to global development outcomes. The establishment of the SDG 6, ensuring the availability and sustainable management of water and sanitation for all, reflects increased attention to water and sanitation on the global development agenda. The pillars of the SDG 6 are: achieving universal access to safe and affordable drinking water and sanitation by 2030, improving water quality, wastewater treatment and safe re-use, increasing water-use efficiency to ensure water security, especially in water-stressed areas, and implementing integrated water resource management and adequate financing to meet the SDG 6 targets (United Nations, 2018).

According to the United Nations (2018), most countries are struggling to meet the SDG 6 targets. Despite this, the proportion of the global population using at least a basic drinking water service increased from 81% in the year 2000 to 89% in 2015. The proportion of the global population using at least a basic sanitation service increased from 59% in 2000 to 68% in 2015. Water quality problems are largely associated with developing countries; however, most countries have implemented integrated water management practices.

Table 1 shows that South Africa is a water scarce and rainfall deprived country compared with the rest of the world, which makes South Africa a good candidate for analysis. This is also affirmed by Masindi & Duncker (2016). The country only receives 465 mm or 50% of the rainfall received by most countries in the world annually. Given its high reliance on surface water, there is a need to manage existing resources efficiently. In a study projecting the temperature and precipitation changes for the African continent for two future time periods, 2030–2059 (near term) and 2070–2099 (long term), Almazroui *et al.* (2020) projected a continuous and significant increase in the mean annual temperature over all of Africa and its eight sub-regions during the twenty-first century and a decline in precipitation over the southern parts of Africa. This provides further evidence of dwindling water resources in Africa and South Africa.

Table 1. | South African water sector indicators and progress on SPG Goal 6.

Water resources availability and security	17% deficit: 3,800 million m^3/a by 2030
	Average annual rainfall of 465 mm (half of the world average)
	Total annual runoff of approximately 49,000 million m^3/a of which 63% is stored in large dams
	The current reliable yield of surface water at an acceptable assurance level of supply: 10,200 million m^3/a nationally
	3,000 million m^3/a is from ground water
	61% of water is used by agriculture and 39% by domestic, industry, afforestation and other sectors
Water and sanitation access	Of 16.9 million households, 15.2 million or 89.9% have access to piped water with 83% having access to safe drinking water 64% of households have reliable access to water supply services
	Average domestic water use is around 237 litres per person per day (world average: 173 litres per person per day)
	10.3 million or 61% of households have access to sewage connected flush toilets, with the additional 37% having access to some form of sanitation. Only 14.1 million households have access to safe sanitation.
	Non-revenue water: 1,660 million m^3 per year, R9.9 billion each year
Financing gap	R33 billion each year

Authors' table adapted from DWS (2019).

According to the Department of Water and Sanitation (DWS) (2019), South Africa is facing a water crisis caused by insufficient water resources, and poor infrastructure maintenance and investment. The DWS alludes to plans to diversify the sources of water where water security is to be derived from ground water, water conservation and water demand management (given the high levels of technical distribution water losses – excluding non-technical losses like billing inefficiencies and non-collection – of more than 1,660 million m^3/a), water re-use, desalination and effective cross-boundary water management. The DWS estimates the water infrastructure investment deficit to be R33 billion per annum (about $2.2 billion). The quality of rivers and ground water remains poor, signalling weaknesses in water resource management.

In terms of water use, the DWS (2019) reported that agriculture uses 61% of allocated water, while municipalities use 27%. The remainder is consumed by other sectors, such as energy, industries, mining, livestock and forestry. As it relates to universal access to basic water services, South Africa is among the countries that are performing relatively well. Table 1 indicates that of the 16.9 million households or total population of 59.9 million, 89.9% or 15.2 million households have access to piped water (also see Figure 1), while 61% or 10.3 million households have access to flush toilets complemented by the other forms of sanitation. The Achilles Heel of the South African water sector is inadequate management of infrastructure; for example, the DWS (2019) indicated that approximately 56% of over 1,150 municipal wastewater treatment works (WWTWs) and approximately 44% of 962 water treatment works (WTWs) in the country are in a poor or critical condition, and 11% of this infrastructure is completely dysfunctional. This poor management results in average technical distribution water losses of 36% or 1,660 million m^3 by municipalities and 7% by the water boards. On the consumption side, South African water users consume 237 litres per capita per day and 64 litres more than the average global daily consumption.

The water sector value chain is comprised of national water resources, regional bulk, and local retail water and sanitation services segments (Figure 2). According to Masindi & Duncker (2016), the DWS is the designated custodian of water resources by the National Water Act. It leads policy development and regulates the water and sanitation sector in South Africa. It is also responsible for planning and implementation of large water resource infrastructure projects, issuing of water-use licenses, allocating water, and performing catchment management functions, river system management, water storage, and abstraction and return-flow management. At a regional

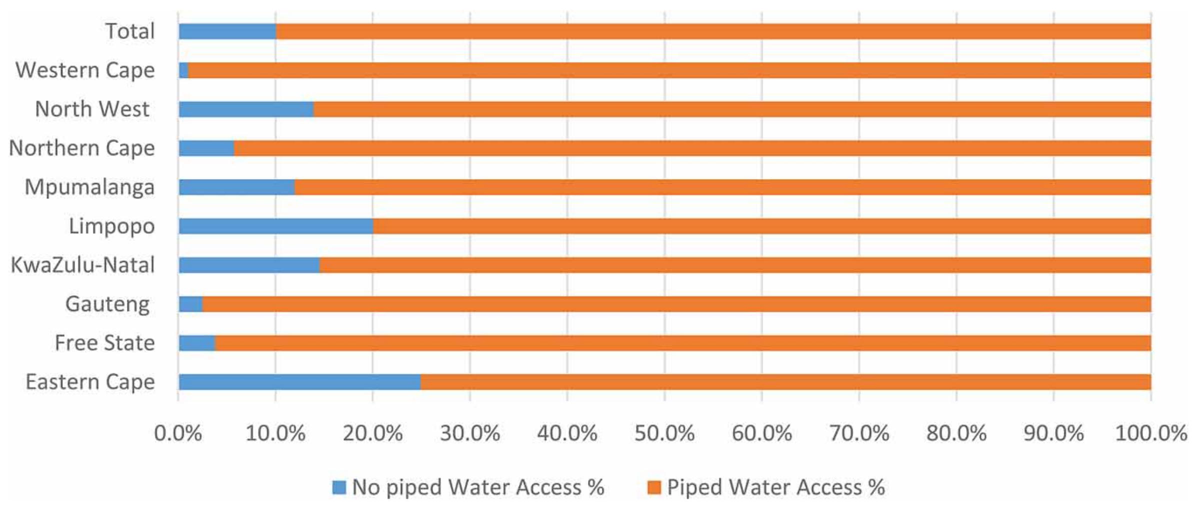

Fig. 1. | Provincial household access to water. *Source:* Authors' graph adapted from Statistics South Africa (2016).

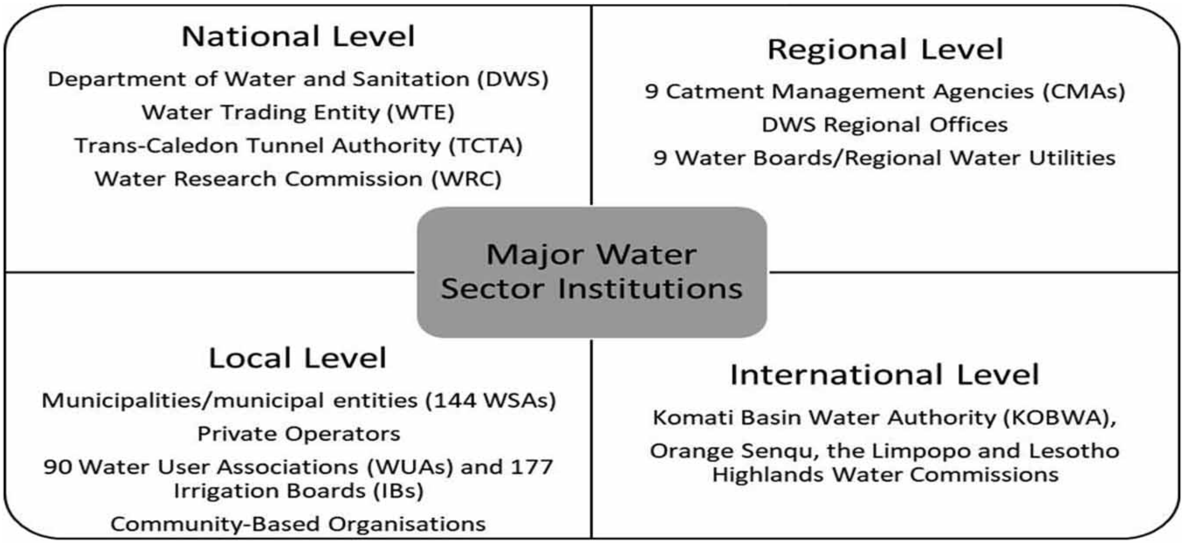

Fig. 2. | Water sector institutional and role players. *Sources:* Authors' diagram adapted from DWS (2019) and Beck *et al*. (2016).

level, according to Masindi & Duncker (2016), there are nine water boards mainly responsible for bulk water purification and distribution; however, some municipalities and the DWS also perform this function. The National Treasury (2019) stated that water boards are mandated by the Water Services Act to provide bulk industrial and potable water services to municipalities and industries within their legislated areas of supply. The water boards vary in size, activities, customer mix, revenue base and operational capacity. As opposed to municipalities, the bulk distribution networks of water boards are generally in good condition, with acceptable levels of total water losses (about 7%), showing good management of infrastructure. In terms of the Constitution, municipalities have sole powers to reticulate water to households. However, where there is no capacity to deliver, they appoint other service providers such as water boards and private sector operators to implement on their behalf. The mandates of the water institutions are summarised in Table 2, which also outline their high-level operational performance.

Masindi & Duncker (2016) and DWS (2019) indicated that some challenges facing the water boards, municipalities and DWS include weak governance, lack of adequate funding coupled with inefficient operations to meet and sustain investment requirements, inappropriate financing and pricing arrangements, and lack of accountability. Moreover, water is severely under-priced and cost recovery is not being achieved. This results in ineffective operations and the maintenance of water supply infrastructure. Gupta *et al.* (2012) advised that if the water and sanitation supply revenue from user charges falls short of expenditure (financing and investment gap), it causes assets to deteriorate and threatens the sustainable supply of water and sanitation services.

According to Table 2, the scale of operations of municipal water businesses in the water and sanitation services supplies space performed by approximately 146 authorised municipalities and exceeds that of the nine water boards. The consolidated water revenue and expenditure of these municipalities is three times that of the nine water boards; however, the carrying value of assets of the water boards is two times larger than that of the municipalities. According to the DWS (2018), the DWS, water boards and municipalities, and other state departments own about 854 dams, mostly with high storage capacity, and the private sector owns about 4,657 small dams. From Table 2, it is further evident that the nine water boards own large bulk distribution pipelines, reservoirs,

Table 2. | Summary of operations of key water sector institutions, 2020/2021.

Institutions	Mandate	Revenue (R'000)	Expenditure (R'000)	Carrying value of assets (R'000)	Net volumes
DWS	The DWS is responsible for water sector policy, support and regulation. Wholly funded by the national government	17,000,000	17,000,000	2,000,000	
WTE	The WTE deals with the management of water infrastructure and resources, and the sale of raw water. Largely funded from water tariffs and augmented through the national budget for public interest functions. The Department's asset register indicates a total pipe network of 1,070 km and canal systems of 8,100 km. Of the 5,248 registered dams in South Africa, the DWS/WTE only owns 6% (320), but they account for 86.4% of the retained water	16,000,000	14,000,000	98,000,000	19,142 million m^3/a sold
TCTA	The TCTA is responsible for financing and implementing the development of bulk raw water infrastructure, and providing treasury management services to the DWS. The authority plays an important role in providing: financial advisory services such as structuring and raising project finance, managing debt and setting tariffs; project implementation services; and other technical support to the department and water boards. Funded through the WTE from raw water sales revenue.	5,000,000	6,000,000		
9 CMAs	The CMA's mandate is the management of water resources. Funded from water resource management charges and losses subsidised by the DWS through the WTE	753,000	753,000		19,142 million m^3/a managed
9 Water Boards	Water Boards provide water services (bulk potable and bulk waste water) to other water service institutions. They own large bulk distribution pipelines, reservoirs, and water and waste water treatment plant and serve municipalities and industries	29,000,000	24,000,000	75,000,000	2,528 million m^3/a sold net losses of 7%
146 Municipalities	Authorised municipalities (WSAs) are responsible for bulk and retail water supply. They purchase bulk water from water boards or directly from the DWS. Municipal water reticulation infrastructure includes more than 290,000 km of pipelines supplying water to 89.9% of the population.	76,000,000	69,000,000	33,400,137	4,980 million m^3/a produced, 36% or 1,660 million m^3/a lost
Total		143,753,000	130,753,000	208,400,137	

Authors' table adapted from National Treasury (2020a, 2020b), DWS (2019), Statistics South Africa (2020, 2016), Beck *et al*. (2016) and Water Research Commission (2012).

and water and waste water treatment plants used to serve municipalities and industries. Municipal water reticulation infrastructure includes more than 290,000 km of pipelines currently supplying water to 89.9% of the population. In terms of the volumes produced and sold, the water boards sell about 2,528 million m^3 per annum after accounting for 7% average distribution losses while municipalities produce 4,980 million m^3 per annum, but sell about 3,187 million m^3 per annum after accounting for 36% average technical losses. This implies that water boards provide about 50% of municipal bulk water requirements while municipalities self-produce the remainder. The Water Trading Entity (WTE), Catchment Management Agencies (CMAs) and the Trans-Caledon Tunnel Authority (TCTA) collectively construct and manage water resource assets such as dams, canals, pipelines and conveyancing systems valued at R98 billion producing and distributing 19,142 million m^3 per annum, of which 61% is used by the agricultural sector and the rest by other sectors, including municipalities and water boards as reported earlier.

We analyse the technical efficiency of water boards by applying a non-parametric benchmarking tool called Data Envelopment Analysis (DEA). DEA is ideal to measure and compare the technical efficiency of the nine water boards as they operate in similar conditions. It is easy to compare their production technologies to determine efficiency. Gupta *et al*. (2012) recommended the use of DEA for determining the technical efficiency of decision-making units (DMUs). They argued that despite other techniques such as the ordinary least square (OLS) and stochastic frontier analysis (SFA) being used in analysing the technical efficiency of the water industry, DEA is the most appropriate. The OLS technique is easy to use and simple to interpret; however, it suffers from the problem of specifying the functional form for the production technology and is unable to provide information on frontier performance. The SFA, although able to solve the latter problem by specifying a composed error term and splitting the error term into two different parts as a data noise term and error due to the inefficiency, also suffers from the problem of specifying the functional form and requires specification of the distribution patterns of the inherent error terms. DEA is devoid of these deficiencies. The aims of the study are achieved by analysing data related to expenditure used by the nine water boards and the efficiency outcomes they achieve during the study period, 2018/2019, in producing the prevailing bulk water volumes at going tariff rates while taking into consideration water losses. We provide policy-makers with information on how well a particular water board is performing relative to its peers, identifying good and bad practices, and finally finding more efficient approaches to achieve financial sustainability and reliable water and sanitation supply in the pursuance of national and SDG 6 objectives.

It is clear that the South African water value chain is inextricably linked with the water resources and water and sanitation service components complementing each other. Despite the financial value of the municipal water business being the largest in the value chain, their efficiency in the supply of water and sanitation services has been widely studied (see Murwirapachena *et al*. (2019), Brettenny & Sharp (2016), Monkam (2014), Mahabir (2014) and Dollery & Van der Westhuizen (2009)). These studies suffer from specification bias insofar as it concerns the production technology as undesirable outputs are modelled as inputs. Studies on the technical efficiency of water boards in South Africa are also not available, except for a paper by Ngobeni & Breitenbach (2020). For this reason, we opted to analyse the efficiency of water boards in South Africa. Our paper differs from the paper by Ngobeni & Breitenbach (2020) in that we use a methodology developed by You & Yan (2011) to adequately include a very significant undesirable (bad) output related to water provision, namely water losses, in our model (ratio model), and we compare the results with traditional models to illustrate the biased efficiency results from the traditional models. You and Yan have shown that the results from their model provide results superior to other methods of dealing with undesirable outputs. This is discussed more fully under the methodology section.

The rest of the paper is organised as follows: Sections 2 and 3 deal with the literature and methodological specification, respectively, Section 4 with the data, Section 5 with the results and Section 6 concludes the study.

2. LITERATURE REVIEW

As stated above, DEA has been extensively used globally to analyse technical efficiency in the water sector. However, to the best of our knowledge, this is the maiden study to use DEA or any other modelling technique to analyse the efficiency of water boards in South Africa while considering 'bad outputs' like water losses which are a central feature of such production processes. In regards to the water sector efficiency literature, we deal firstly with a very brief summary of international studies in the water sector to illustrate the type of models as well as the inputs and outputs used. Thereafter, we discuss the most important literature on the South African water sector.

2.1. International

Ali *et al.* (2018) used the constant returns to scale (CRS) along with an input-minimisation DEA to analyse the performance of four water supply units in Pakistan over a 3-year period (2013–2015). The study adopted a six-variable production technology consisting of two outputs (number of consumers served and revenue) and four inputs (management, maintenance, operations and energy costs). Lannier & Porcher (2014) used an input-minimisation DEA based on the variable returns to scale (VRS) in stage 1 and a SFA in stages 2 and 3. They assessed the relative technical efficiency of 177 water supply DMUs in France. Revenue was used as a proxy for costs. The volume of billed water, number of customers and length of water pipes were used as outputs. Network performance was included as a quality output. Kulshrestha & Vishwakarma (2013) used a DEA model to determine the water supply efficiency of 20 urban municipalities in the state of Madhya Pradesh, in India. Three input-oriented DEA models were used in the efficiency evaluation. Each model had three outputs (number of connections, length of distribution network and average daily water production), while the number of inputs varied from one to three (staff per 1000 connections, operating expenditure and non-revenue water) consecutively in each model. Another study by Gupta *et al.* (2012) applied an output-oriented DEA model to assess the productive efficiency of urban water supply systems in 27 selected Indian cities. The study used expenditure as an input and total water served by a water utility as a function of revenue, expenditure and water production capacity. Singh *et al.* (2014) applied DEA to determine the relative efficiency of 12 selected Indian urban water utilities (municipal bodies) of Maharashtra state/province. They used an input-oriented CRS DEA model with total expenditure and staff size as two inputs and water supplied and the number of connections as two outputs. Marques *et al.* (2014) applied DEA to 5,538 observations of 1,144 utilities that supplied drinking water between 2004 and 2007 in Japan. The models considered three inputs and two outputs. The inputs included capital, staff and other operational expenditures. For outputs, the volume of water and the number of customers were adopted.

2.2. South Africa

As it pertains to South Africa, Brettenny & Sharp (2016) studied the efficiency of 88 authorised water services like local and metropolitan municipalities. The paper used an input-oriented DEA with operating costs and system input volume as sole input and output variables. Of the 44 urban water service authorities, 10 were efficient under the VRS and four under the CRS. Of the rural water service authorities, five were efficient under the VRS and only one under the CRS. The performances yielded an average technical efficiency of 63.6% for urban municipalities and 52.6% for rural municipalities. Murwirapachena *et al.* (2019) adopted DEA, SFA and stochastic non-parametric envelopment of data (StoNED) methods to analyse efficiency based on cross-sectional data from 102 South African water utilities in the period 2013/2014. They obtained varying results under the different methods: StoNED (MM): 68.1%, SFA: 66.2% and DEA: 44.7% for all utilities, 58.7% for the big ones and 46.1% for the small utilities. The analytical variables used in the study were total cost as a single input, water output, total connections and the length of mains as outputs, with the population serving as an environmental output variable. In another paper, Monkam (2014) used DEA and SFA to analyse the efficiency of 231 local municipalities in South Africa. The study adopted municipal operating expenditure as an input and five output variables: the four basic services and total population per municipality. The results showed stark variation in efficiency scores between municipalities.

Mahabir (2014) used the Free Disposable Hull technique to measure the technical efficiency of 129 municipalities in the provision of water from 2005 to 2009. Six analytical variables were selected, and the study concluded that over the period, four municipalities remained constantly efficient. The average technical efficiency score was 0.3 in 2005/2006, peaking at 0.39 in 2007/2008, and declining to 0.35 in 2008/2009. Dollery & Van der Westhuizen (2009) used DEA to determine the productive efficiency of 231 local municipalities and 46 district municipalities in the delivery of basic services covering the period 2006/2007. The study determined the efficiency estimates under the CRS and the VRS, embracing output-orientated and input-orientated approaches. Under the output-orientated approach, the district municipalities were, on average, only 30.5% efficient under the CRS, 58% efficient under the VRS and 48% scale efficient. In terms of local municipalities, those with the highest average technical efficiency scores under the output-maximisation and input-minimisation measures for both the CRS and VRS were in Gauteng, with respective average technical efficiency scores of 67.7, 79.4, 67.7 and 76.7%.

3. METHODOLOGY

In this paper, we use the VRS approach reported by Gavurova *et al.* (2017) and developed in 1984 by Banker, Charnes and Cooper to allow for consideration of scale efficiency analysis. This is called the Banker, Charnes and Cooper (BCC) model. The terminology 'envelopment' in DEA refers to the ability of the efficiency production frontier to tightly enclose the production technology (input and output variables). Cooper *et al.* (2007) and McWilliams *et al.* (2005) stated that DEA was developed in a microeconomic setting and applied to firms to convert inputs into outputs. However, in efficiency determination, the term 'firm' is often replaced by the more encompassing DMU. DEA is an appropriate method of computing the efficiency of institutions employing multivariate production technologies. Aristovnik (2012) and Martić *et al.* (2009) stated that there are input-minimisation and output-maximisation DEA models. The former determines the quantity of inputs that could be curtailed without reducing the prevailing level of outputs. The latter expands the outputs of DMUs to reach the production possibility frontier while holding inputs constant. However, the selection of each orientation is study-specific. In this paper, we select the input-minimisation orientation for the four models. DEA basically erects a production frontier consisting of most relatively technically efficient DMUs in the sample. This process generates technical efficiency measures for each unit in the sample by comparing observed values with optimal values of outputs and inputs. A score of 1 represents the best-performing unit in the sample and a score of less than 1 implies that the unit is not performing as well as its efficient peers. DEA determines how much inputs could have been saved and the extent of outputs that could have been improved by inefficient DMUs by emulating the production processes of efficient DMUs.

According to Taylor & Harris (2004), DEA is a comparative efficiency measurement tool that evaluates the efficiency of homogeneous DMUs operating in similar environmental conditions; for example, DMUs dealing with bulk water supply and where the relationship between inputs and outputs is unknown. Wang & Alvi (2011) report that DEA only uses the information used in a particular study to determine efficiency and does not consider exogenous factors. DEA measures the distance of production functions by determining the radial extent of DMUs to the efficiency frontiers. It does so by categorising the DMUs into extremely efficient and inefficient performers. In terms of the DEA methodology, the current study uses the BCC model with the ratio of DMUs complying with the norms of at least being two to three times the combined number of inputs and outputs.

3.1. Treating undesirable outputs

DEA models have found increasing use in efficiency analysis applications where at least one output in the production process is an undesirable output, e.g. pollution or water losses. There is considerable research published on the undesirable aspects of production outputs. However, You & Yan (2011) have found that the economic implications and the suitability of DEA models incorporating the undesirable outputs should be carefully considered as the results may either under- or overstate efficiency if modelled incorrectly. Breitenbach *et al.* (2020) recently used this approach to consider the efficiency of healthcare systems in managing the COVID-19 pandemic and used deaths and infections as undesirable outputs.

The first way that undesirable outputs are dealt with in the traditional DEA model is to ignore the undesirable output (Nakashima *et al.*, 2006; Hua & Bian, 2007; Lu & Lo, 2007a, 2007b). It is not, however, appropriate to ignore the reality of, e.g., pollution or water losses during production since undesirable outputs and desirable outputs are generated simultaneously in the production process. Dyckhoff & Allen (2001) dealt with undesirable outputs by modelling them as inputs. However, treating undesirable outputs as inputs fails to reflect the true production process, which is the same approach adopted by Ngobeni & Breitenbach (2020). There is a specific production technology that links inputs to outputs, and taking an undesirable output as an input in the production process leads to misspecification and misinterpretation, for example, when modelling the pollution as an input using an output-oriented measure, ecological inefficiencies remain undetected. Golany & Roll (1989) suggested a data transformation approach where an undesirable output is converted into a 'normal' output by a monotonic decreasing function. The undesirable outputs (carbon and nitrogen emissions) are treated as normal outputs by taking their reciprocals. Although the pollutant is treated as output, the scale and intervals of the original data get lost and the problem with zero values is that they do not have a reciprocal value. The linear monotonic decreasing transformation was suggested by Seiford & Zhu (2002). A sufficiently large positive scalar β_i is added to the reciprocal additive transformation of the undesirable output i, so that the final values are positive for each DMU_k. This model is criticised for its invariance to data transformation within the DEA model (Lu & Lo, 2007a, 2007b). Färe *et al.* (1989) treat undesirable factors in a non-linear DEA model based on the weak disposability of undesirable outputs (Zhou *et al.*, 2007). Weak disposability assumes that to reduce undesirable outputs is costly, because simultaneously it increases the inputs or decreases desirable outputs (Yang *et al.*, 2008). It tends to increase the desirable output and undesirable output concurrently. Regardless of the form of transformation, as long as the final value of undesirable output included in the DEA calculation remains positive, it increases the efficiency of the DMU. An undesirable output should bring either a negative or positive impact to the performance of DMU; therefore, it is not appropriate for the undesirable output to solely favour the efficiency score.

After comparing the performance of the models discussed above, You & Yan (2011) developed the ratio model, which outperformed all five of these models developed for dealing with undesirable outputs. We therefore opted to adopt the ratio model for the current paper. The ratio model is different from the previous approaches in that the undesirable output is aggregated in a ratio form with the desirable output. From the conventional BCC DEA model and assuming that there are R DMU_r ($r = 1, 2, \ldots, R$), that convert m inputs to n outputs, DMU_k is one of the R DMUs being evaluated. It is further assumed that DMU_k consumes m inputs X_t^k ($i = 1, 2, \ldots, m$) to produce n outputs Y_j^k ($j = 1, 2, \ldots, n$) and all these outputs are assumed to be desirable. The measure of the efficiency of DMU_k is then obtained by:

min θ subject to

$$\sum_{r=1}^{R} \lambda_r X_i^r - \theta X_i^k + s_i^- = 0 \quad i = 1, 2, \ldots, m \tag{1}$$

$$\sum_{r=1}^{R} \lambda_r Y_j^r - s_j^+ = Y_j^k \quad j = 1, 2, \ldots, n \tag{2}$$

$$\sum_{r=1}^{R} \lambda_r = 1$$

$$\lambda_{r,} \ s_i^-, \ s_j^+ \geq 0 \quad r = 1, \ \ldots, \ R \tag{3}$$

where DMU_r = the rth DMU, r = 1,2, …, R; DMU_k = the kth DMU being evaluated; X_i^r, Y_j^r = the inputs and outputs of every DMU_r; i = 1, 2, …, m, j = 1,2, …, n; θ = the efficiency of DMU_k; λ_r = the dual variable corresponding to the other inequality constraint of the primal; s_i^-, s_j^+ = the slack variables that turn the inequality constraint into an equal form; $\lambda_{r,}^*$ s_i^{-*}, s_j^{+*} = the optimal solutions when the relative efficiency of DMU_k is $\theta^* = 1$ and $s_i^{-*} = s_j^{+*} = 0$.

In the ratio model, the undesirable output and desirable output are defined as O_q^- $(q = 1, 2, \ldots, n_1)$ and O_p^+ $(p = 1, 2, \ldots, n_2)$, respectively $(n_1 + n_2 = n)$. For $\mathrm{DMU}_{k,}$ the undesirable outputs $O_q^-(q = 1, 2, \ldots, n_1)$ are treated as a new variable ψ_k, which is called the penalty parameter and is written as:

$$\psi_k = \rho_1 O_{1k}^- + \ldots + \rho_{n1} O_{n1k}^- \tag{4}$$

where ψ_k = penalty parameter for DMU_k; ρ_q = the penalty for individual undesirable output $(q = 1, 2, \ldots, n_1)$; and O_q^- = the undesirable output $(q = 1, 2, \ldots, n_1)$. Since ρ_q is the penalty charged for producing the outputs, the ψ_k obtained from problem (4) gives a measure of the total monetary value of undesirable outputs. From the definition of ψ_k, the greater the amount of undesirable output, the greater the value of the penalty parameter. Furthermore, the respective value of ρ_q is associated with the individual undesirable output; therefore, ρ_q has the same value for every DMU. With this model, desirable and undesirable outputs can relate to one another, regardless of disagreement in the units. With the new approach of treating the undesirable outputs in (4), the desirable output p $(p = 1, 2, \ldots, n_2)$ of DMU_k in the ration model is modified as:

$$Y'_\rho = \frac{1}{\psi_k} O_p^+, \quad (p = 1, 2, \ldots, n_2) \tag{5}$$

where O_p^+ = the desirable output $(p = 1, 2, \ldots, n_2)$; Y'_ρ = the modified output $(p = 1, 2, \ldots, n_2)$.

The ratio model computes desirable and undesirable outputs as fractions, where undesirable output O_q^- is the denominator and desirable output O_p^+ the numerator. Here, the value of the output is interpreted as a ratio of desirable to undesirable output. Using ratios provides a simple and easy way to expose the impact of undesirable outputs in a DEA. The ratio form of the DEA model can satisfy the restrictions of the conventional DEA, which the output variable states must be a positive value. Moreover, the ratio form provides a more distinct way for the desirable output to describe the presence of an undesirable output on DMU efficiency.

In order to check the stability of our model results, we ran four different model specifications and compared the results. In Model I, we use expenditure as financial input, bulk water tariffs as financial output and water losses (bad output) and bulk water sales volumes as physical outputs (we ignore the effect of bad outputs). In Model II, we use the same variables while excluding the water losses variable from the model (we use only good outputs, ignoring the bad output). In Model III, we use expenditure as the financial input and the ratio of bulk water tariffs to water losses and bulk water sales volumes to water losses as physical outputs (ratio model). Model IV uses expenditure as financial input and water losses as a physical input, bulk water tariffs as financial output and bulk water sales volumes as physical output (we use the bad output as an input).

4. DATA

Our data were obtained from different sources. The data for the total expenditure, water losses (technical and non-technical) and bulk water tariffs were extracted from the 2018/2019 audited annual reports of the water boards and volumes sold were obtained from the National Treasury (2020b). The sample consists of the nine water boards, one financial input: expenditure, one financial output: bulk water tariffs and two physical outputs (water losses and volumes sold). From Table 3, it is clear that there is substantial variation between the variables with Rand Water an outlier at the higher end and Overberg an outlier at the lower end of the spectrum.

The standard deviation is therefore quite large with most variables. For example, with expenditure, the mean value is R2,148,354 with a maximum of R12,221,051 and a minimum of R52,006, whereas volumes sold has a mean value of 294,594 million m^3/a with Rand Water an outlier at the higher end of 1,714,308 million m^3/a and Overberg an outlier at the lower end of the spectrum of 3,265 million m^3/a. The water board utilities are dominated by three large water boards, while the rest have relatively small shares of the market.

5. RESULTS

The results of the four model variants are provided in Table 4. The mean technical efficiency scores of the nine DMUs range between 29 and 79% across the four variant models, implying the need to improve efficiency by 21–71% by the inefficient DMUs in all models. The average technical efficiency score is the same when water losses are included and omitted in Models I and II, respectively. In line with You & Yan (2011), we conclude that Model variants I and II do not accurately capture the state of technology and that by omitting the bad output or by modelling the bad output as a positive output, we cannot accept the results as a true reflection of the state of

Table 3. | Data and descriptive statistics.

Water boards	Expenditure (R'000)	Water losses (%)	Bulk water tariffs (R/kl)	Volumes sold (million m^3/a)
Amatola Water	434,914	14	11	31,432
Bloem Water	757,552	9	8	81,118
Lepelle Water	656,372	5	6	89,440
Magalies	609,125	6	7	92,321
Mhlathuze	624,985	4	4	45,106
Overberg Water	52,006	9	7	3,265
Rand Water	12,221,051	3	9	1,714,308
Sedibeng Water	1,590,743	8	9	122,551
Umgeni Water	2,388,440	2	7	471,801
Mean	2,148,354	7	8	294,594
Standard deviation	3,621,058	4	2	518,709
Minimum	52,006	2	4	3,265
Maximum	12,221,051	14	11	1,714,308

Sources: National Treasury (2018, 2019, 2020b), Amatola Water (2019), Bloem Water (2019), Lepelle Northern Water (2015), Magalies Water (2019), Mhlathuze Water (2019), Overberg Water (2019), Sedibeng Water (2019), Rand Water (2019) and Umgeni Water (2019).

Table 4. | Technical efficiency scores.

Water Board	Model I	Model II	Model III	Model IV
Amatola	1.00	1.00	0.16	1.00
Bloem	0.66	0.66	0.18	0.20
Lepelle	0.73	0.73	0.34	0.08
Magalies	0.81	0.81	0.33	0.09
Mhlathuze	0.42	0.42	0.26	0.08
Overberg	1.00	1.00	**1.00**	1.00
Rand	1.00	1.00	**1.00**	0.02
Sedibeng	0.48	0.48	0.13	0.15
Umgeni	1.00	1.00	**1.00**	0.02
Mean	0.79	0.79	**0.49**	0.29
No. of efficient units	4	4	3	2

Sources: DEA efficiency results.

technology and technical efficiency outcomes. The efficiency results in Models I and II are therefore hugely overstated. In Model III (the ratio model), the mean technical efficiency score of water boards is **49%**.

That is, with the correct inclusion of water losses as an undesirable output, the average technical efficiency score declines by 30%. Put differently, ignoring the bad output (water losses) by just including or omitting it as an output in the water board production process overstates the average technical efficiency score by 30%. This is a substantial distortion of the efficiency estimates. Model IV is the last of the input-minimisation model variants; it shows that using a bad output (water losses) as an input (as in Ngobeni & Breitenbach, 2020) completely alters the production technology by decreasing the average technical efficiency of water boards by 20% to a score of 29%. Therefore, just incorporating a negative output as an input materially underestimates the efficiency scores. As a result, we follow You & Yan (2011) and adopt the best-performing Ratio Model III for the discussion of the results and formulation of the recommendations associated with the input-minimisation objective. Using the other three input-minimisation models (Models I, II and IV) does not accurately capture a crucial undesirable output (water losses) and is an inappropriate DEA application that may lead to incorrect conclusions and policy recommendations. The lower technical efficiency scores obtained for water boards across all the models are in line with the results by Murwirapachena *et al.* (2019), Brettenny & Sharp (2016), Monkam (2014), Mahabir (2014) and Dollery & Van der Westhuizen (2009) for municipal water and sanitation supply services in South Africa.

Their results also overestimated the technical efficiency scores when bad outputs were not considered as in our Models I and II. Overall, this implies that the general technical efficiency of municipalities may be much lower than previously believed. In regard to water boards, we have shown above that by modelling water losses as an undesirable output, true efficiency is lower than if we choose to omit it in our estimation or incorrectly model it as a positive output. This has important policy implications when technical efficiency is substantially lower than initially thought and estimated and policy actions also based on these over- or understated efficiency values.

The above technical efficiency results do not mean much if not interpreted together with the inefficiency factors (radials and slacks). Coelli *et al.* (2005) defined slacks as input excesses and output shortfalls that are required over and above the initial radial movements to push DMUs to efficiency levels. Both the slack and radial movements are associated only with the inefficient DMUs.

The radial movements are initial input contractions or output expansions that are required for a firm to become efficient. Therefore, using the Model III results, the average technical inefficiency rate is 51% with the six inefficient water boards needing to reach the optimal efficiency frontier depicted by the Overberg, Rand and Umgeni water boards. Table 5 summarises the efficiency and inefficiency rates as they relate to expenditure. The input minimisation implies using the same or fewer inputs while maintaining the same levels of outputs. For Model III, the inefficiency rate of 51% is equivalent to wastage in expenditure of R3.7 billion by the six inefficient water boards. The three efficient water boards serve as peers for the inefficient ones. Given the input and output variables that comprise the model and the production structure, it is therefore easy to see that the main reason for the poor performance of the inefficient water boards is the high operating expenditure relative to the efficient water boards like Umgeni Water, holding output levels constant. Given the high levels of water and sanitation coverage backlogs in provinces where the inefficient water boards operate and the financing gap for the water sector, it is proposed that the individual inefficient water boards conduct a detailed review of their expenditure items such as personnel and operational costs through a benchmarking exercise with the efficient peers for improvements, which may reveal more detailed reasons for the inefficiency. The prospective savings from moving to the efficiency frontier could also be used to extend service coverage, given the backlogs in service delivery depicted in Figure 1. Therefore, the study recommends efficiency improvements that could assist to achieve the SDG 6 targets and objectives.

In order to illustrate the relative inefficiency of the smaller water boards below the inefficiency frontier more clearly, one can perform a simple comparison with one of the larger water boards that operate on the efficiency frontier. In Table 6, we chose to compare three of the smaller water boards with Umgeni Water – the second largest water board that also happens to be scale efficient. We only discuss two of them to illustrate the relative inefficiency.

Table 5. | Radial and slack movements.

Water Board	Prevailing spending (R'000)	Inefficient spending (R'000)	Rate of inefficiency (%)	Benchmarked efficient spending (R'000)	Rate of efficiency (%)	DMU peers for improvements
Amatola	434,914	– 364,239	– 84	70,675	16	Overberg and Umgeni
Bloem	757,552	– 619,741	– 82	137,811	18	Umgeni and Overberg
Lepelle	656,372	– 430,526	– 66	225,846	34	Umgeni and Overberg
Magalies	609,125	– 408,087	– 67	201,038	33	Umgeni and Overberg
Mhlathuze	624,985	– 464,717	– 74	160,268	26	Umgeni and Overberg
Overberg	52,006	–	0	52,006	100	Overberg
Rand	12,221,051	–	0	12,221,051	100	Rand
Sedibeng	1,590,743	– 1,390,380	– 87	200,363	13	Umgeni and Overberg
Umgeni	2,388,440	–	0	2,388,440	100	Rand
Total	19,335,188	***– 3,677,690***	***– 51***	15,657,498	49	

Sources: DEA efficiency results from National Treasury (2018, 2019, 2020b), Amatola Water (2019), Bloem Water (2019), Lepelle Northern Water (2015), Magalies Water (2019), Mhlathuze Water (2019), Overberg Water (2019), Sedibeng Water (2019), Rand Water (2019) and Umgeni Water (2019).

Table 6. | Inputs and outputs relative to the benchmark (Umgeni Water).

Water Board	VRSTE	Total expenditure (R)	Water losses (%)	Bulk water tariff (R)	Volumes sold (million m^3/a)
Umgeni Water	1	2,388,440	2	7	471,801
Amatola Water	0.16	434,914	14	11	31,432
Bloem Water	0.18	757,552	9	8	81,118
Lepelle Water	0.34	656,372	5	6	89,440
Comparison with Umgeni					
Amatola/Umgeni		0.182091239	7	1.571428571	0.066621309
Bloem/Umgeni		0.31717439	4.5	1.142857143	0.171932658
Lepelle/Umgeni		0.274812011	2.5	0.857142857	0.189571451

Source: Calculated from model results and raw data.

From Table 6, the inefficiency of the smaller water boards becomes more apparent. Amatola Water with an efficiency score of only 16%, for example, has a total expenditure of 18% of that of Umgeni, but sells only 6.7% of the quantity sold by Umgeni. Amatola also has seven times the proportion of water losses compared with Umgeni and charges 1.5 times the tariff of Umgeni. In the case of Lepelle Water, which has an efficiency score of 34%, total expenditure is 27% of that of Umgeni Water, yet they only sell 18.9% of the volume sold by Umgeni. Water losses are 2.5 times that of Umgeni, but they do, however, have a lower water tariff than Umgeni.

Of more importance in the case of the water boards, however, is the scale efficiency of the water boards' production technology. The average scale efficiency scores of water boards across the four models range from 62 to 92%. As illustrated in Figure 3, the highest scale efficiency scores are recorded in Model III. The most prevalent form of scale is the increasing returns to scale (IRS) (there is potential to improve the extent of operations: an increase in inputs will result in a more than proportional increase in output). Only the Overberg and Umgeni water boards were scale efficient in Model III. The only water board with a scale efficiency of less than 50% is Rand Water. The other water boards surpass the 95% scale efficiency mark.

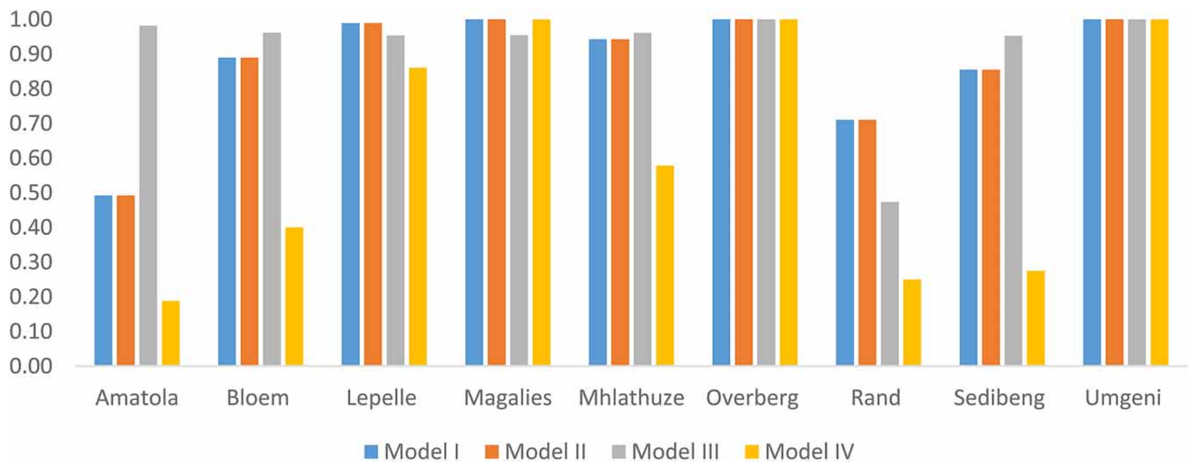

Fig. 3. | Scale efficiency scores. *Source:* DEA efficiency results.

Only the Rand and Sedibeng water boards recorded decreasing returns to scale (an increase in inputs will lead to a less than proportional increase in output: the extent of operations is bigger than required). Therefore, the water boards operating on the IRS frontier could combine the efficiency savings with private financing or future tariff increases to improve the scale of their operations and expand operational footprint. Those operating at decreasing returns to scale (DRS) should benchmark with the scale efficient water boards for improvements. In sum, we are not recommending a reduction in the current expenditure levels of all water boards despite some being inefficient. We are recommending the efficient use of resources to improve the current operational levels. This implies improved scale efficiency for the seven water boards that are scale inefficient. Policy-makers should also consider fast-tracking the reform to merge some of the smaller- to medium-sized water boards into large regional water utilities as they operate on less than optimal scale. This is an ideal water board's model for operations, funding and sustainability. However, this reform should be preceded by a detailed benchmarking of operational practices with peer water boards to avoid merging inefficient operations.

6. CONCLUSIONS

The study used four comparative input-oriented DEA models to analyse the technical efficiency of the nine water boards' expenditure efficiency while maintaining the current levels of bulk water tariffs and sales volumes. We used a novel DEA ratio model developed by You & Yan (2011), which treats undesirable outputs by dividing the positive outputs (tariffs and volumes) by water losses to convert them into a ratio that eliminates biased efficiency estimates. Only 3 or 33% of the water boards were efficient. Despite six water boards being inefficient, the inefficiency rate was 51% due to the much larger water boards – Rand and Umgeni Water – accounting for the bulk of the spending and water supply in the sector. Given the results from the scale efficiency, the main policy implication is that the smaller water boards would need to increase the scale of operations to become scale efficient, while the largest and third largest water boards are experiencing decreasing returns to scale, meaning that they need to reduce their scale of operations to attain scale efficiency. The results suggest that holding the outputs fixed, six small- to medium-sized water boards could be merged after an efficiency benchmarking exercise to improve scale efficiency. The results from the scale efficiency seem to support larger regional water boards as small- to medium-sized water boards are scale inefficient.

In this paper, we have demonstrated the importance of modelling bad or undesirable outputs by comparing the results of the ratio model with other model variants as suggested by You & Yan (2011). Our results (in line with You & Yan (2011)) confirm the fact that the ratio model more accurately captures the impact of undesirable outputs in the production technology on technical efficiency and eliminates over- and underestimation resulting from incorrect specification of the production technology in traditional models. This method can therefore be recommended for policy applications in other country studies or cross-country studies in the water sector with confidence, regardless of the water management conditions. The study is constrained in several ways. DEA results are heavily dependent on the selection of analytical variables and accuracy of statistics. However, the results of Models I and II show that variations in results from different production technologies could be insignificant to non-existent. The material factor in DEA analysis is the correct treatment of desirable and undesirable inputs and outputs, as reflected by Models III and IV.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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