Environmental Science & Policy 61 (2016) 116–123

Contents lists available at ScienceDirect

Environmental Science & Policy

journal homepage: www.elsevier.com/locate/envsci

Assessing the efficiency of Chilean water and sewerage companies accounting for uncertainty

María Molinos-Senante[a,b,c,*], Guillermo Donoso[d,e], Ramon Sala-Garrido[f]

[a] Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago, Chile
[b] Facultad de Arquitectura e Instituto de Estudios Urbanos, Pontificia Universidad Católica de Chile, El Comendador 1916, Santiago, Chile
[c] Centro de Desarrollo Urbano Sustentable CONICYT/FONDAP/15110020, Av. Vicuña Mackenna 4860, Santiago, Chile
[d] Departamento de Economía Agraria, Pontificia Universidad Católica de Chile, Casilla 306-22, Santiago, Chile
[e] Centro de Derecho y Gestión del Agua, Pontificia Universidad Católica de Chile, Casilla 306-22, Santiago, Chile
[f] Departamento de Matemáticas para la Economía y la Empresa, Universidad de Valencia, Avd. Tarongers S/N, Valencia, Spain

ARTICLE INFO

Article history:
Received 12 August 2015
Received in revised form 29 February 2016
Accepted 3 April 2016
Available online xxx

Keywords:
Data envelopment analysis (DEA)
Efficiency
Ranking
Uncertainty
Water utilities

ABSTRACT

Efficiency assessment of water and sewerage companies (WaSCs) has attracted considerable attention both for water company managers and water regulators. Within the methodological approaches that can be applied to estimate efficiency scores, data envelopment analysis (DEA) is the most widely applied technique. In spite of the positive features of DEA, it presents a major drawback which is its deterministic nature. In other words, conventional DEA models do not account for uncertainty in the data. To overcome this limitation, we assess, for the first time, the efficiency of a sample of Chilean WaSCs by using a DEA model with statistical tolerance in the data. Hence, 81 efficiency scores are estimated for each WaSC rather than a single score as with conventional DEA models. The results illustrate that outputs exhibit larger uncertainty than inputs. Moreover, WaSCs efficiency scores change significantly under the best-case and worst-case scenarios. The ranking of the WaSCs allows for the identification of which of them has the highest performance based on their efficiency scores. This information is essential to enhance efficiency and innovation in the water industry. Moreover, the introduction of uncertainty in the efficiency assessment allows for the prediction and ranking of future performance of WaSCs.

1. Introduction

Over the last few years, efficiency assessment in water industry has attracted considerable attention by researchers, water companies and regulators (Romano and Guerrini, 2011). Improvement of the efficiency of water companies is desirable allowing for cost reduction, increase profits of water companies, and/or decreased prices paid by consumers for water and sewerage services (Molinos-Senante et al., 2015a). Hence, improvement of efficiency is a major policy objective of water companies and regulators (Carvalho and Marques, 2011).

Most studies that assess the efficiency of water utilities employ the non-parametric data envelopment analysis (DEA) (e.g., García-Sánchez, 2006; Berg, 2010; Molinos-Senante et al., 2014). The advantages of DEA are that: (i) it does not require assumptions about the functional relationship between inputs and outputs; (ii) it allows for the estimation of the efficiency of productive decision making units (DMUs) which use multiple inputs to produce multiple outputs; and (iii) the weights to aggregate inputs and outputs are generated endogenously which minimizes the subjectivity of the assessment (Guerrini et al., 2013).

In spite of these advantages, DEA is not exempt of limitations. The deterministic nature of DEA is a major drawback, as statistical inferences cannot be drawn from conventional DEA models (Ananda, 2014) and efficiency scores are highly sensitive to atypical observations and data errors (De Witte and Marques, 2010). To take into account uncertainty in the efficiency assessment, several methodological approaches have been developed (Li, 1998; Simar and Wilson 1998, 2007; Cazals et al., 2002; Daraio and Simar, 2005; Bonilla et al., 2004).

In spite of the importance of considering uncertainty in efficiency assessment in the framework of water utilities, the information gap in the literature is evident. To the best of our knowledge, only De Witte and Marques (2010); Ananda (2014) and See (2015) applied bootstrapping techniques to evaluate the

* Corresponding author.
E-mail addresses: mmolinos@uc.cl (M. Molinos-Senante), gdonosoh@uc.cl (G. Donoso), sala@uv.es (R. Sala-Garrido).

http://dx.doi.org/10.1016/j.envsci.2016.04.003
1462-9011/

efficiency of water companies. Sala-Garrido et al. (2012) used DEA with tolerances model to assess the efficiency of a sample of Spanish wastewater treatment plants accounting for uncertainty. In view of the few empirical applications which deal with the uncertainty issue in the performance measurement of water companies, there is a clear need for advancing in this research stream.

Efficiency scores are often used to identify which units use resources most efficiently. However, to make informed decisions the evaluated DMUs should be ranked in terms of efficiency. According to DEA methodology, several DMUs can be identified as efficient and therefore, they cannot be ranked directly by using their efficiency scores (Esmaeilzadeh and Hadi-Vencheh, 2015). Hence, several methodological approaches have been proposed to deal with the issue of ranking DMUs (Adler et al., 2002) such as cross-efficiency (Sexton et al., 1986), benchmarking approaches (Torgersen et al., 1996), multivariate statistical tools (Friedman and Sinuany-Stern, 1997), super-efficiency (Andersen and Petersen, 1993), and efficiency indicators (Boscá et al., 2011). While each one of these methodological approaches has advantages and shortcomings, the system of indicators proposed by Boscá et al. (2011) were developed specifically to rank DMUs when the efficiency assessment accounts for uncertainty in the inputs and/or outputs.

Against this background, the objectives of this paper are threefold. The first one is to identify which variables (inputs and/or outputs) are the most sensitive to changes, i.e., which have the largest potential uncertainty. The second objective is to evaluate the efficiency of a sample of water and sewerage companies (WaSCs) accounting for uncertainty. The empirical application focuses on the 23 main Chilean WaSCs for 2014. The third objective of this paper is to rank the evaluated WaSCs to support the decision process of water regulators.

This paper contributes to the current strand of literature in the field of water companies' performance measurement by computing the efficiency scores of WaSCs introducing statistical tolerances in the data and by ranking the WaSCs based on their efficiency scores. To the authors' knowledge, this is the first study that applies DEA with a tolerances model to assess the efficiency of a sample of WaSCs accounting for uncertainty. Chile presents an interesting case within the context of this research since it has long been a pioneer in the privatization of water and sewerage services. Chile has been by far the most successful case of water and sewerage services privatization after the privatization of the English and Welsh water companies in the 1980s (Lee and Floris, 2003). Moreover, because Latin America could be described as being situated at a medium level in terms of coverage and quality of water and sewerage services, water managers and authorities in other Latin American countries can learn some lessons from the Chilean case (Molinos-Senante et al., 2015a, 2015b, 2015c; Molinos-Senante and Sala-Garrido, 2015). On the other hand, the Chilean tariff law introduced the concept of an efficient water and sewerage operator model, so as to incentive providers to be technically and economically efficient. Additionally, privatization of WaSCs in Chile have led to lower rates in the long term since its rate setting system has allowed for the transfer of efficiencies to final prices. Thus, it is of interest to assess the effectiveness of these regulatory reforms on WaSCs' efficiency, so as to extract lessons and implications for its potential replication.

From a policy perspective, this study is of great interest both for WaSCs' managers and water regulators. On the one hand, the inclusion of variability in the data allows WaSCs that should be on alert to be identified, since small changes in the inputs and/or outputs will cause a significant reduction in their efficiency. On the other hand, the ranking of the WaSCs based on efficiency scores is essential for water regulators to promote competition between the WaSCs reducing monopoly problems. This issue is essential to ensure the sustainability of WaSCs over time and to provide improved water and sewerage services to citizens.

2. Methodology

2.1. Efficiency assessment

DEA is a non-parametric method based on linear programming that allows for the construction of the efficient production frontier based on the inputs and outputs of the DMUs (Charnes et al., 1978). The relative efficiency for each DMU is calculated by comparing its inputs and outputs in relation to the rest of the units (Molinos-Senante et al., 2014). In other words, DEA produces measurements of the relative inefficiency of each DMU when compared to what amounts to an industry's best practice output/input ratio (Cooper et al., 2004). Further details on DEA methodology are provided by Cooper et al. (2007) and Zhu (2015).

Traditional DEA models can be input-oriented or output-oriented. Accordingly, when a DMU reaches the maximum output given a set of inputs (output-oriented DEA) or uses a minimum of inputs to produce a given set of outputs (input-oriented DEA) it is placed on the production frontier and therefore, it is efficient (Cooper et al., 2004). The selection of the orientation depends on the objective of the efficiency evaluation. Following past evidence (Guerrini et al., 2011; Mahmoudi et al., 2012; Carvalho and Marques, 2014), in this study an input orientation was adopted since the aim of the WaSCs is to provide water and sewerage services minimizing the use of inputs.

In DEA framework, the production frontier can be estimated by considering constant returns to scale (CRS) and variable returns to scale (VRS) technologies. The CRS approach assumes that all DMUs operate at an optimum level. On the other hand, the VRS approach compares DMUs with a similar scale. Molinos-Senante et al. (2015a) investigated whether Chilean WaSCs operate under CRS or VRS technology. They concluded that the technology of the WaSCs in Chile is overall CRS at a confidence interval of 95%. Hence, in this paper we assumed that the DMUs evaluated have CRS technology.

Given $k = 1, 2 \ldots, n$ DMUs (WaSCs in our case study), teach one using a vector of M inputs $x_k = (x_{1k}, x_{2k}, \ldots, x_{Mk})$ to produce a vector of S outputs $y_k = (y_{1k}, y_{2k}, \ldots, y_{Sk})$, according to the model DEA-CRS, the measure of efficiency θ is obtained by solving for each DMU k_0 the following linear programming problem:

$$\begin{array}{ll} \text{Min}\theta & \\ s.t. & \\ \sum_{k=1}^{n} \lambda_k x_{ik} \le \theta x_{ik_0} & 1 \le i \le M \\ \sum_{k=1}^{n} \lambda_k y_{rk} \ge y_{rk_0} & 1 \le r \le S \\ \lambda_k \ge 0 & 1 \le k \le n \end{array} \tag{1}$$

where λ_k is a vector of intensity. The measure of efficiency θ is bounded between 0 and 1. It is considered that a DMU (WaSC in our case study) is efficient if $\theta = 1$, while it is inefficient if $0 \le \theta < 1$. The difference between the score θ and the value of 1 can be considered to be the potential reduction in inputs to obtain the same set of outputs.

Eq. (1) illustrates the traditional DEA model developed by Charnes et al. (1978) with input orientation and CRS technology assumption. In essence, the efficient input–output levels in DEA are those which are not dominated by the others in the reference set. The applied analysis presupposes data determinism and, so, any mistake or inaccuracy in the measure could alter the efficiency index results, a common limitation of efficiency analyses based on DEA.

To overcome this limitation, we applied a DEA model with statistical tolerance developed by Bonilla et al. (2004) which has been applied by other authors such as Boscá et al. (2009, 2011);

Medal (2010); Sala-Garrido et al. (2012); Perez and Gomez (2014). Methodologically, the linear programming model Eq. (1) is solved where each input and output is altered by the inclusion of a tolerance level. The tolerance levels are calculated based on the differences between the maximum and the minimum and the mean for each DMU. Thus, following Bonilla et al. (2004) we focused on the most favorable case scenario and least favorable case scenario for each DMU. The most favorable case (optimistic scenario) for WaSC k_0 results from decreases and increase of inputs and outputs, respectively, while the rest of the WaSCs present the inverse behavior in their variables according to tolerance levels defined. On the other hand, the least favorable case (pessimistic scenario) for the WaSC k_0 occurs when inputs increase and outputs decrease, while for the rest of WaSCs, inputs decrease and outputs increase. The maximum and minimum values of the confidence interval of the new efficiency scores that solve Eq. (1) under the best and worst possible case scenarios allows for the analysis of the consistency of the efficiency score values; the smaller the interval the greater the consistency in the score values.

The application of this methodology can be summarized in the following steps:

Step 1: Choice of the methodological approach to determine the tolerance values of the inputs and outputs.

The definition of the tolerance values is essential for the DEA model accounting for uncertainty. There are two main alternative approaches to define the tolerances of the data such as the use of generic and random variations and the use of historical series of inputs and outputs. While both approaches are meaningful, Medal and Sala (2009) through the analysis of contingency tables of the distribution of scores for each DMU, concluded that the selection of tolerances based on individual historical variations in the inputs and outputs leads to better results than the use of random variations. According to Boscá et al. (2011) the tolerances defined for each of the outputs and inputs may be symmetrical or not respect to the original value.

Taking into account the historical variations in the data and main characteristics of the WaSCs evaluated in this study, it was considered more appropriate to define asymmetric tolerances for the inputs and outputs of the WaSCs.[1]

Step 2: Estimation of tolerance values for each input and output.

Tolerance values should be defined for each input and output. They are non-negative scalar values and express the changes from left and right of the values of the inputs and outputs as follows:

Tolerance for inputs: α_{ik} and α'_{ik}

Tolerance for outputs: β_{rk} and β'_{rk}

According to the tolerance values defined, the values of the inputs and outputs are within the following range (Sala-Garrido et al., 2012):

$$\begin{matrix} x_{ik} \in [x_{ik} - \alpha_{ik}, x_{ik} + \alpha'_{ik}] \\ y_{rk} \in [y_{rk} - \beta_{rk}, y_{rk} + \beta'_{rk}] \end{matrix} \quad (2)$$

Step 3: Selection of the DEA combinations to be solved.

According to Eq. (2), there is a breadth number of possible combinations of inputs and outputs. Hence, it is not feasible to calculate efficiency scores for all of them. In order to simplify the analysis and obtain representative, understandable and useful results, we focused our assessment on analyzing the original and extreme values of each input and output, following Medal (2010). Hence, to evaluate the efficiency of the WaSC k_0, the inputs and outputs take the following values:

$$\begin{matrix} \text{Inputs of the WaSC}: & x_{ik_0}(1-\alpha_{ik_0}), x_{ik_0}, x_{ik_0}(1+\alpha'_{ik_0}) \\ \text{Outputs of the WaSC}: & y_{rk_0}(1-\beta_{rk_0}), y_{rk_0}, y_{rk_0}(1+\beta'_{rk_0}) \\ \text{Inputs of the WaSC} & k \neq k_0 : x_{ik}(1-\alpha_{ik}), x_{ik}, x_{ik}(1+\alpha'_{ik}) \\ \text{Outputs of the WaSC} & k \neq k_0 : y_{rk}(1-\beta_{rk}), y_{rk}, y_{rk}(1+\beta'_{rk}) \end{matrix} \quad (3)$$

[1] Methodologies for the calculation of symmetric and asymmetric tolerance level for each input and output are described as supplementary information.

According to Eq. (3), there are 3^4 (81) DEA combinations that should be solved for each WaSC k_0. They are the result of three situations: (i) favorable; (ii) unfavorable, and (iii) original, with four possible inputs and outputs: (i) inputs for the analyzed WaSC; (ii) outputs for the analyzed WaSC; (iii) inputs for the remaining WaSCs; and (iv) outputs for the remaining WaSCs.

Step 4: Estimation of the efficiency scores for each WaSC taking into account the tolerance values.

This step involves the replacement of the original values by the modified values according to the estimated level of tolerance in the DEA model (Eq. (1)). As a result, for each WaSC k_0, two extreme scenarios are defined, namely: (i) optimistic or best-case scenario; and (ii) pessimistic or worst-case scenario.

$$\text{Optimistic scenario}: x_{ik} = \left\{ \begin{matrix} x_{ik_0} - \alpha_{ik_0} \\ x_{ik} + \alpha'_{ik} \end{matrix} \right. y_{rk} = \left\{ \begin{matrix} y_{rk_0} + \beta'_{rk_0} \\ y_{rk} - \beta_{rk} \end{matrix} \right. \quad (4)$$

$$\text{Pessimistic scenario}: x_{ik} = \left\{ \begin{matrix} x_{ik_0} + \alpha'_{ik_0} \\ x_{ik} - \alpha_{ik} \end{matrix} \right. y_{rk} = \left\{ \begin{matrix} y_{rk_0} - \beta_{rk_0} \\ y_{rk} + \beta'_{rk} \end{matrix} \right. \quad (5)$$

As is shown in Eq. (4) the optimistic scenario for the WaSC k_0 implies that inputs decrease and outputs increase for this WaSC, while the rest of the WaSCs present the inverse behavior in their variables according to tolerance levels defined. On the other hand, the pessimistic scenario for the WaSC k_0 defined in Eq. (5) determines that for this WaSC, inputs increase and outputs decrease, while the for the rest of WaSCs, inputs decrease and outputs increase. Thus, under the optimistic and pessimistic scenarios, the maximum and minimum efficiency scores are obtained for each WaSC evaluated. Hence, the DEA model with tolerances allows us to narrow the uncertainty in efficiency assessment.

2.2. Ranking of water companies

One of the objectives of efficiency assessment is benchmarking the DMUs evaluated, i.e. ranking DMUs according to their efficiency scores. As was reported in the introduction, since several WaSCs can be identified as efficient, they cannot be ranked directly. As Boscá et al. (2011) illustrated, ranking DMUs requires the development of efficiency indicators based on the scores previously quantified. Accordingly, we followed the methodological approach developed by Boscá et al. (2011) to rank WaSCs according to its efficiency scores.

The two efficiency indicators for the k_0-th order WaSC are defined as follows (Boscá et al., 2011):

$$R^1_{k_0} = \frac{e_{k_0}}{\tau_{k_0}} \quad (6)$$

$$R^2_{k_0} = \begin{cases} \dfrac{S_{k_0} - e_{k_0}}{\tau_{k_0} - e_{k_0}} if \, \tau_{k_0} \neq e_{k_0} \\ 0 if \, \tau_{k_0} = e_{k_0} \end{cases} \quad (7)$$

where e_{k_0} is the number of times that WaSC k_0 has an efficiency score equal to 1, i.e., the number of times that the WaSC k_0 is efficient; τ_{k_0} is equal to 81 since it is the number of DEA combinations solved for each WaSC; and S_{k_0} is the sum of the 81 efficiency scores of WaSC k_0.

$R^1_{k_0}$ is bounded between 0 and 1 and reports the proportion of times that WaSC k_0 is efficient. A value of 0 means that in none of the 81 scenarios evaluated the WaSC k_0 is efficient. By contrast, a $R^1_{k_0}$ equal to 1 means that the WaSC has been identified as efficient in all evaluated cases. Hence, the higher the value of $R^1_{k_0}$, the higher the propensity that the WaSC is efficient (Sala-Garrido et al., 2012). The indicator $R^2_{k_0}$ is also bounded between 0 and 1 and it is used to rank WaSCs when two have the same value for the first $R^1_{k_0}$ indicator,

3. Sample description

In the last twenty-five years, the Chilean water industry has implemented significant reforms (Molinos-Senante et al., 2015a, 2015b, 2015c; Molinos-Senante and Sala-Garrido, 2015). First, in 1990 the national water regulator, namely "Superintendencia de Servicios Sanitarios" (SISS), was created. Second, by the end of 1998 the privatization of the water industry was started. Thus, from 1998 to 2000, a significant part of the capital of six of the main Chilean WaSCs was privatized (SISS, 2014). Third, from 2001 to 2004 the rights for the exploitation of some WaSCs were transferred to private companies. As a result of the privatization of the Chilean water industry in 2014, 95.7% of customers were supplied by private WaSCs (SISS, 2014).

According to SISS (2014), in 2014 there were 53 water companies operating in the 15 Chilean regions providing water and sewerage services to 16 million people. The sample studied in this research consists of 23 of the main Chilean WaSCs which provide water and sewerage services to approximately 98% of the total number of urban customers (SISS, 2014). Statistical information is extracted from the management reports of water and sewerage services published by SISS for the year 2014.

The considered objective of a WaSCs is to perform a productive process that supplies drinking water and collects and treats wastewater according to the required quality criteria by legislation at the lowest possible cost. Accordingly and following past evidence, three inputs were considered in this study: (i) operating costs (x_1) which are the water and sewerage industry's total operating expenditure (except labor) (See, 2015), such as expenditures related to operation, maintenance and administration of the urban water cycle; (ii) labor (x_2) expressed as the numbers of employees (Mbuvi et al., 2012), including both direct and external workers who carry out tasks for the WaSCs but do not belong to the companies (Molinos-Senante et al., 2015a) and; (iii) network length (x_3) (Coelli and Walding, 2006). Selecting a variable which represents capital expenditure is complicated by valuation disparities. To overcome this problem, previous studies (Ananda, 2014; See, 2015) used the length of the delivery and sewerage networks as proxy for capital input.

Regarding outputs, the most widely used output variable is distributed water volume (De Witte and Marques, 2010; Guerrini et al., 2013). However, the water companies evaluated in this study not only supply drinking water but also provide sewerage and wastewater treatment services. Moreover, it should be highlighted that an important aspect of the urban water cycle is the quality of the services provided. To improve water quality, WaSCs may incur in considerable expenditures (Ananda, 2014). Hence, quality issues cannot be ignored in the assessment of the efficiency of WaSCs (Molinos-Senante et al., 2015b). Following Saal et al. (2007) and Molinos-Senante et al. (2015c) two quality-adjusted outputs were used. The first one is the water distributed (expressed in thousands of cubic meters) adjusted by its quality (y_1). The second output is the number of customers with access to wastewater treatment services adjusted by the quality of the treated water (y_2). Both indicators of quality (drinking water and wastewater treatment) are provided by the SISS for each $[0-1]$WaSC and have a range between

A value of 1 means that the water company has fulfilled all legal requirements regarding quality issues. The construction of the quality-adjusted outputs is as follows:

$$y_1 = VDW \times QDW \tag{8}$$

$$y_2 = CWW \times QTW \tag{9}$$

where y_1 is the quality-adjusted drinking water output; VDW is the volume of drinking water put into the delivery network; QDW is the quality indicator of the drinking water; y_2 is the quality-adjusted wastewater treatment output; CWW is the number of customers with wastewater treatment services and; QTW is the quality indicator of the treated water.

As is illustrated in Eqs. (8) and (9), a value lower than 1 for QDW and QTW penalizes water companies since it involves a reduction in the generation of outputs. Table 1 provides a snapshot of the statistical data used to compute the efficiency scores of Chilean WaSCs.

A limitation in any DEA model is the number of DMUs analyzed in relation to the number of inputs and outputs. Hence, whether a large set of inputs and outputs is considered, relative efficiency discrimination across units will tend to become blurred, as there will exist some dimension in accordance to which DMU will be defined as efficient (Tupper and Resende, 2004). To avoid this problem, "Cooper's rule" must be taken into account in the selection of inputs and outputs. Accordingly, the number of units to be evaluated must be larger than or equal to $\max\{m \times s; 3(m+s)\}$ where m is the number of inputs and s is the number of outputs involved in the DEA study (Cooper et al., 2007). In this study, 23 WaSCs were analyzed while the number of inputs was three and the number of outputs was two. Hence, "Cooper's rule" was obeyed.

In our research, both inputs and outputs are subject to uncertainty. For example, while operating costs are strictly controlled by WaSCs, it is very difficult to obtain accurate information about them since each WaSCs provides the data to the water regulator only to set water tariffs. Furthermore, sometimes it is complicated to have precise knowledge of the network length due to new urban developments. The situation is

Table 1
Sample description.

	Inputs			Outputs			
	Operating costs (10^3 CLP)	Labor (Nr workers)	Network length (Km)	Water distributed (10^3 m^3)	Customers with wastewater treatment service	Indicator of drinking water quality	Indicator of wastewater treatment quality
Average	27,832,382	590	3138	47,979	688,434	0.954	0.990
SD	38,983,020	765	4941	93,080	1,314,390	0.073	0.014
Minimum	988,941	32	7	653	6,820	0.744	0.950
Maximum	162,769,722	3032	21,481	442,991	6,152,000	1.000	1.000

Source: Own elaboration from Chilean *Superintendencia de Servicios Sanitatios* (SISS) 2014 report.

Table 2
Right and left tolerances for inputs and outputs in% respect to original data.

		Inputs (%)			Outputs (%)	
		Operating costs	Labor	Network length	Quality-adjusted drinking water output	Quality-adjusted wastewater treatment output
Right tolerances in% respect to original data	Average	5.2	3.3	1.5	15.7	20.8
	SD	3.4	3.0	2.2	21.0	27.1
	Minimum	0.8	0.4	0.1	0.4	0.5
	Maximum	13.3	11.5	9.6	75.7	96.2
Left tolerances in% respect to original data	Average	0.1	−1.4	0.1	−6.1	−7.3
	SD	1.8	2.1	0.3	10.5	9.8
	Minimum	−4.5	−8.1	−0.8	−24.7	−24.8
	Maximum	2.5	1.9	0.6	3−0	1.4

more complex with respect to outputs since they involve quality issues. First, water meters are inaccurate in measuring the volume of water put into the delivery network. For example, Arregui et al. (2015) reported errors up to 32% in conventional water meters. Second, both quality indicators are based on the determination of pollutants in the water. While the precision of analytical methods has considerably improved in recent years, occasional analytical mistakes may produce data that are not representative.

4. Results and discussion

4.1. Estimation of the tolerances for outputs and inputs

To estimate asymmetrical gaps for each of the outputs and inputs of each WaSC we used data of the last five years, i.e., from 2010 to 2014. Since it was considered more suitable to estimate asymmetric tolerances, we computed right tolerances which involve an improvement of outputs and a worsening of inputs and left tolerances which implies a worsening of outputs and an improvement of inputs (Table 2). Tolerances are interpreted as follows: the larger value of the tolerance, the larger sensitivity of the input or output to changes. In other words, tolerances reflect the potential data uncertainty.[2]

Table 2 illustrates that the average value of tolerance for outputs is larger than for inputs. This means that the greatest uncertainty in the evaluation of the performance of WaSCs is associated to the volume of water supplied and wastewater treated considering quality issues. Thus the outputs involved in this study are not directly controllable by the WaSCs but depend mainly on customers demand. By contrast, inputs exhibit less uncertainty than outputs since they are directly managed by WaSCs. With respect to the outputs, the highest variability is observed in the number of customers with access to wastewater treatment. This is because in recent years Chilean WaSCs and the water regulator have made significant efforts to increase the coverage of wastewater treatment services. Regarding inputs, the network length is the input with the lowest variability since in 2010 urban water coverage was close to universal that year.

At the water company level, both right and left tolerances are highly variable especially for outputs as is supported by the standard deviation values presented in Table 2. As is illustrated, right tolerances are significantly more variable than left tolerances. For example, for the number of people with access to wastewater treatment services, focusing on right tolerances, the minimum value was 0.5% (WaSC 19), while the maximum value was 96.2% (WaSC 11). This variability in the tolerance values for this variable reflects the different efforts that WaSCs have made to improve the coverage and quality of wastewater treatment services in recent years. It is also important to note that both outputs are weighted by the quality of the service provided by the WaSC. Hence, the tolerance values are influenced not only by quantity but also by quality issues.

4.2. Efficiency scores of water and sewerage companies

Once the tolerances for inputs and outputs for the 23 WaSCs were calculated, the next step in our assessment was to estimate efficiency scores. To improve the understanding and interpretation of the results, we focused on four scenarios: (i) original efficiency scores calculated without tolerances labeled as “original”; (ii) maximum efficiency score obtained which corresponds to the optimistic scenario labeled as “max”; (iii) minimum efficiency scores which corresponds to the pessimistic scenario labeled as “min” and; (iv) mean efficiency score of the 81 combinations with tolerances labeled as “mean”. Table 3 shows the efficiency scores for the 23Chilean WaSCs evaluated for the 4 scenarios. Moreover, information on the amplitude of the range (max-min) and (original-mean) is also reported.

As is shown in Table 3, 6 out of 23 WaSCs (26%) are efficient when scores are computed using original data. This means that these water companies cannot reduce the use of inputs keeping the production of outputs if they are compared with the other evaluated WaSCs. Hence, these 6 WaSCs comprise the benchmark of the best practice. This figure is consistent with the results reported by Molinos-Senante et al. (2015a) who concluded that for 2012, 28% of the Chilean WaSCs were efficient. Nevertheless, it should be considered that they used other variables as outputs including undesirable outputs. The large standard deviation of the estimated efficiency scores should be highlighted. As a result of the large disparity in efficiency scores across the evaluated water companies, the mean efficiency score of the sample of WaSCs is 0.527. This finding implies that the potential for input saving among WaSCs is about 47.3%.

Under the most optimistic scenario (max), the average efficiency score of WaSCs could potentially reach 0.581 which means that there could be an improvement in efficiency of approximately of 41.9%. Moreover, under this most favorable scenario, 9 out of 23 WaSCs (39%) are identified as efficient. This means that there are three water companies which are efficient in the optimistic scenario but not in the original one. These WaSCs are the closest ones to currently be efficient since in the best-case scenario they become efficient. By contrast, 13 out of 23 WaSCs (56%) would not become efficient, even in the optimistic scenario.

If the pessimistic scenario is analyzed, only 1 out of 23 WaSCs is efficient. It should be highlighted that 5 of the 6 water companies

[2] Tolerance values for each water and sewerage company are shown as Supplementary information.

Table 3
Efficiency scores for the 23 main Chilean water and sewerage companies accounting for uncertainty.

WaSC	Original	Max	Min	Mean	Max-min (%)	Original-Mean (%)
1	0.3613	0.3676	0.1211	0.2803	24.6	8.1
2	1.0000	1.0000	0.3748	0.8632	62.5	13.7
3	0.7861	1.0000	0.2785	0.6741	72.1	11.2
4	0.1769	0.1852	0.0586	0.1392	12.7	3.8
5	0.1380	0.1415	0.0428	0.1058	9.9	3.2
6	1.0000	1.0000	0.3316	0.8134	66.8	18.7
7	0.2136	0.2455	0.0708	0.1730	17.5	4.1
8	0.1612	0.1687	0.0528	0.1264	11.6	3.5
9	0.5177	0.8998	0.1606	0.4905	73.9	2.7
10	1.0000	1.0000	0.3791	0.8649	62.1	13.5
11	1.0000	1.0000	0.5622	0.9041	43.8	9.6
12	0.6082	1.0000	0.1934	0.5920	80.7	1.6
13	1.0000	1.0000	0.3462	0.8559	65.4	14.4
14	0.9497	1.0000	0.3064	0.8307	69.4	11.9
15	1.0000	1.0000	1.0000	1.0000	0.0	0.0
16	0.2430	0.2522	0.0612	0.1777	19.1	6.5
17	0.4100	0.4250	0.0980	0.2940	32.7	11.6
18	0.1369	0.1534	0.0387	0.1080	11.5	2.9
19	0.1707	0.1722	0.0349	0.1188	13.7	5.2
20	0.3200	0.3310	0.0800	0.2321	25.1	8.8
21	0.3958	0.4333	0.0815	0.2874	35.2	10.8
22	0.1866	0.2277	0.0526	0.1212	17.5	3.5
23	0.3478	0.3520	0.0780	0.2438	27.4	10.4
Average	**0.5271**	**0.5807**	**0.2089**	**0.4490**	**37.2**	**7.8**
SD	**0.3510**	**0.3756**	**0.2263**	**0.3248**	**25.8**	**4.9**

that were efficient based on the original data are no longer efficient in the worst-case scenario. Here, it is worth noting that only WaSC number 15 is efficient in the four scenarios. Likewise, it is also important to note the significant decrease in the average efficiency due to the fact that some water companies reduced their efficiency score to less than 0.1. These changes mean that these water companies should be on alert, as if there are small changes in the use of inputs or in the generation of outputs, including quality issues, its efficiency will be greatly negatively affected.

As in the pessimistic scenario, in the mean scenario, only one WaSCs was efficient. This means that this water company is efficient in the 81 DEA combinations. Moreover, the average efficiency for the mean scenario is 0.449 which is similar to the efficiency scores computed with the original data. However, Table 3 shows that the maximum amplitude between the original and mean scores is 18.7%, while the lowest amplitude is 0.0%. These findings mean that when the efficiency of the water industry is evaluated as a whole, the mean value obtained considering uncertainty (81 scenarios) is similar to the one obtained with the original data. However, when the assessment focuses on water company level, accounting for uncertainty acquires special relevance since for some WaSCs there are large differences between the results from original data and from the mean of the 81 scenarios.

Fig. 1 illustrates the variation intervals between the optimistic and pessimistic scenarios of WaSCs efficiency scores, as well as the scores when the original values of inputs and outputs were employed. The different length of the bars denotes the stability level in the obtained results. Thus, a large amplitude implies that the performance of a water company may improve or worsen significantly when its inputs and/or outputs change. By contrast, low amplitude means that the efficiency will change minimally despite variations in the level of inputs and/or outputs. Fig. 1 evidences that there is only one water company that would be efficient in an uncertain context. Moreover, there is another group of WaSCs characterized by low variability, i.e., their amplitudes are small. However, these water companies exhibit low efficiency scores even in the best-case scenario. Hence, they can be considered as “insensitive” water companies in the sense that their performance is little affected by the uncertainty in the data. For the Chilean water industry, the mean amplitude between the optimistic and pessimistic scenarios is 37%. However, water companies are not a homogeneous group. Thus, of the assessed WaSCs, results indicate that 9 out of 23 water companies (39%) exhibit amplitudes larger than 40%, reaching a maximum value of 81%. In contrast, the same percentage of WaSCs, i.e., 39%, have amplitudes lower than 20%.

4.3. Using performance indicators for ranking water and sewerage companies

To rank WaSCs according its performance, the indicators $R^1_{k_0}$ and $R^2_{k_0}$ were computed based on the previously estimated efficiency scores (Boscá et al., 2011). The values of both indicators are shown in Table 4. Results illustrate that WaSC 15 occupies the first place in the ranking since it presents the best performance when uncertainty is introduced in the efficiency assessment. It should

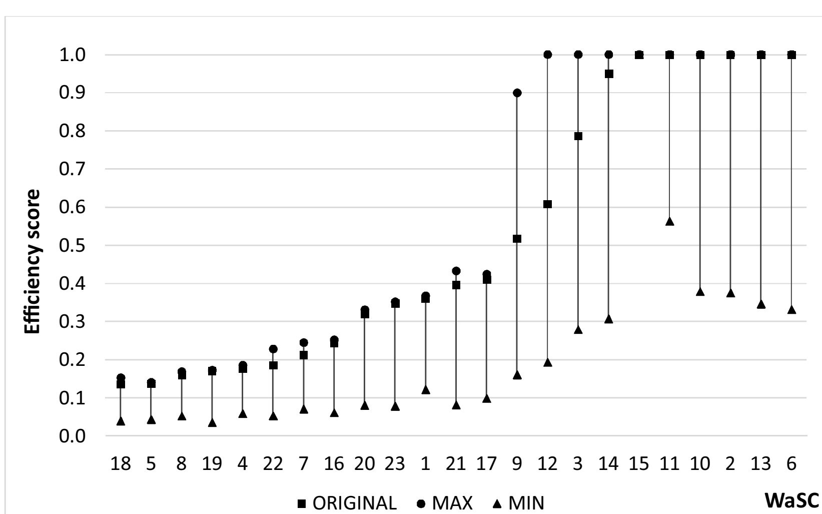

Fig. 1. Efficiency scores with tolerances: maximum, original and minimum scores.

Table 4
Ranking of water and sewerage companies based on efficiency scores.

WaSC	$R^1_{k_0}$	$R^2_{k_0}$
15	1.000	–
11	0.778	0.568
10	0.778	0.392
2	0.778	0.385
13	0.778	0.351
6	0.667	0.440
14	0.333	0.746
3	0.222	0.581
12	0.222	0.475
9	0.000	0.491
1	0.000	0.280
7	0.000	0.173
22	0.000	0.151
4	0.000	0.139
8	0.000	0.126
18	0.000	0.108
5	0.000	0.106
21	0.000	0.029
16	0.000	0.018
19	0.000	0.012
17	0.000	0.003
23	0.000	0.002
20	0.000	0.002

be noted that when efficiency was evaluated using original data (Table 3) 6 out of 23 WaSCs had an efficiency score equal to one, i.e., they were identified as efficient. Hence, it was not possible to identify which of the 6 WaSCs had the best performance. The estimation of the indicator $R^1_{k_0}$ allowed us to overcome such limitation and identify undoubtedly which is the WaSC with the best performance. According to $R^1_{k_0}$ values, the subsequent positions in the ranking are occupied by WaSCs 2, 10, 11 and 13 which have the same value. These WaSCs were efficient in the original and optimistic scenarios. However, in the pessimistic scenario they were inefficient and therefore its $R^1_{k_0}$ value is lower than the unity. Moreover, results $R^1_{k_0}$ confirms that 14 out of 23 WaSCs could never become efficient even in the optimistic scenario since its $R^1_{k_0}$ value equals to zero.

The results of the $R^2_{k_0}$ indicator enabled ranking WaSCs that have the same value of $R^1_{k_0}$.

In particular, as illustrated in Table 4, $R^2_{k_0}$ values allowed for the ranking of WaSCs 2, 10, 11 and 13 whose $R^1_{k_0}$ values were the same. In other words, $R^2_{k_0}$ values are useful to rank WaSCs that with the original data were identified as efficient but have different performance in the pessimistic scenario. Moreover, $R^2_{k_0}$ values allowed us to rank the WaSCs which exhibit a $R^1_{k_0}$ value equal to zero, i.e., WaSCs that even in the optimistic scenario would not become efficient. WaSC 9 occupies the highest position in the ranking, while, WaSC 20 would be the less efficient water company, even in the optimistic scenario.

The ranking of WaSCs is of great interest for water regulators since it allows for the comparison of the performance of water companies facing the same regulatory framework. This issue is especially important in countries or regions in which the process to set water tariffs is based on benchmarking processes. Thus, water regulators are provided with more complete and reliable information for the decision-making process when water tariffs are set considering rewards or penalizations for WaSCs.

5. Conclusions

In recent years, interest in assessing the efficiency of water companies has increased since it has proven to be a useful tool for water company managers and water regulators. From a methodological point of view, to estimate the efficiency scores several approaches can be applied. However, the literature illustrates that the DEA method is the most widely used method to evaluate the efficiency of water companies. While this approach presents many positive features, its deterministic nature is its major drawback since statistical inferences cannot be drawn from conventional DEA. In other words, to estimate efficiency scores, DEA does not account for uncertainty in the data.

To overcome such limitation, this paper for the first time evaluates the efficiency of a sample of WaSCs using a DEA model accounting for uncertainty by introducing statistical tolerances in the data. They are based on historical data and represent the potential variability in the inputs and outputs. By applying this approach, 81 efficiency scores for each WaSC are estimated rather than a single score as with conventional DEA models. This allows water companies to analyze its efficiency under an optimistic and pessimistic scenario. We used estimated efficiency scores to rank the WaSCS with respect to their efficiency accounting for uncertainty.

The results for a sample of 23 Chilean WaSCs provide the following primary results: (i) tolerance values for outputs are larger than for inputs. In particular, the quality-adjusted wastewater treatment output is the variable which exhibits the greatest uncertainty. Tolerance values also evidence the different efforts made by the Chilean WaSCs to improve water and sewerage services; (ii) using original data, 6 WaSCs were identified as efficient while this figure increases to 9 water companies under the optimistic scenario and it is reduced to 1 WaSC in the pessimistic scenario; and (iii) the ranking of the WaSCs illustrates that there is only one WaSC which is identified as efficient in the 81 scenarios evaluated and therefore, it occupies the first position in the ranking of the Chilean WaSCs.

From a policy perspective, several implications can be drawn from the methodology and results of this study. First, in the efficiency assessment of WaSCs it is essential to account for uncertainty in the data. Otherwise, biased results might be obtained leading to incorrect conclusions. This paper illustrates that the DEA model with statistical tolerances is a suitable methodology to deal with uncertainty in efficiency assessment of WaSCs. Second, the assessment of efficiency under an optimistic and a pessimistic scenario allows for the identification of WaSCs whose efficiency might change significantly under small changes in the inputs and/or outputs (including quality issues). Third, the ranking of the WaSCs provides essential information to water regulators to design and implement policies and to promote competition between water companies. This issue is vital to enhance efficiency and innovation in water industries which provide water and sewerage services under a natural monopoly regimen. The ranking of the WaSCs, based on efficiency scores, provides water regulators with improved data to make informed decisions in the process of water tariff setting.

Acknowledgement

The authors would like to thank Conycit through the programme Fondecyt (3150268) for financial support.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.envsci.2016.04.003.

References

Adler, N., Friedman, L., Sinuany-Stern, Z., 2002. Review of ranking methods in the data envelopment analysis context. Eur. J. Oper. Res. 140 (2), 249–265.

Ananda, J., 2014. Evaluating the performance of urban water utilities: robust nonparametric approach. J. Water Resour. Plann. Manage. 140 (9), 04014021.

Andersen, P., Petersen, N.C., 1993. A procedure for ranking efficient units in data envelopment analysis. Manage. Sci. 39, 1261–1264.

Arregui, F.J., Balaguer, M., Soriano, J., García-Serra, J., 2015. Quantifying measuring errors of new residential water meters considering different customer consumption patterns. Urban Water J. (in press).

Berg, S., 2010. Water Utility Benchmarking: Measurement, Methodologies, and Performance Incentive. IWA Publishing, United Kingdom.

Bonilla, M., Casasús, T., Medal, A., Sala, R., 2004. An efficiency analysis with tolerance of the Spanish port system. Int. J. Transp. Econ. 31 (3), 379–400.

Boscá, J.E., Liern, V., Martínez, A., Sala, R., 2009. Increasing offensive or defensive efficiency? An analysis of Italian and Spanish football. Omega 37 (1), 63–78.

Boscá, J.E., Liern, V., Sala, R., MartÍnez, A., 2011. Ranking decision making units by means of soft computing DEA models. Int. J. Uncertain. Fuzziness Knowl.-Based Syst. 19 (1), 115–134.

Carvalho, P., Marques, R.C., 2011. The influence of the operational environment on the efficiency of water utilities. J. Environ. Manage. 92 (10), 2698–2707.

Carvalho, P., Marques, R.C., 2014. Computing economies of vertical integration, economies of scope and economies of scale using partial frontier nonparametric methods. Eur. J. Oper. Res. 234 (1), 292–307.

Cazals, C., Florens, J.-P., Simar, L., 2002. Nonparametric frontier estimation: a robust approach. J. Econ. 106 (1), 1–25.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.

Coelli, T., Walding, S., 2006. Performance Measurement and Regulation of Network Utilities. In: Coelli, T., Lawrence, D. (Eds.), Edward Elgar, Cheltenham, U.K, pp. 29–61.

Cooper, W., Seiford, L., Zhu, J., 2004. Handbook on Data Envelopment Analysis. Kluwer Academic Publishers, Boston.

Cooper, W., Seiford, L., Tone, K., 2007. Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software. Springer.

Daraio, C., Simar, L., 2005. Introducing environmental variables in nonparametric frontier models: a probabilistic approach. J. Product. Anal. 24 (1), 93–121.

De Witte, K., Marques, R.C., 2010. Designing performance incentives, an international benchmark study in the water sector. Cent. Eur. J. Oper. Res. 18 (2), 189–220.

Esmaeilzadeh, A., Hadi-Vencheh, A., 2015. A new method for complete ranking of DMUs. Optimization 64 (5), 1177–1193.

Friedman, L., Sinuany-Stern, Z., 1997. Scaling units via the canonical correlation analysis in the DEA context. Eur. J. Oper. Res. 100 (3), 629–637.

García-Sánchez, I.M., 2006. Efficiency measurement in Spanish local government: the case of municipal water services. Rev. Policy Res. 23 (2), 355–371.

Guerrini, A., Romano, G., Campedelli, B., 2011. Factors affecting the performance of water utility companies. Int. J. Publ. Sect. Manage. 24 (6), 543–566.

Guerrini, A., Romano, G., Campedelli, B., 2013. Economies of scale, scope, and density in the Italian water sector: a two-stage data envelopment analysis approach. Water Resour. Manage. 27 (13), 4559–4578.

Lee, T., Floris, V., 2003. Universal Access to Water and Sanitation: Why the Private Sector Must Participate. Natural Resources Forum, Wiley Online Library.

Li, S.X., 1998. Stochastic models and variable returns to scales in data envelopment analysis. Eur. J. Oper. Res. 104 (3), 532–548.

Mahmoudi, M.J., Fathi, B., Sajadifar, H., Shahsavari, A., 2012. Measuring efficiency of water and wastewater company: a DEA approach. J. Appl. Sci. Eng. Technol. 4 (12), 1642–1648.

Mbuvi, D., De Witte, K., Perelman, S., 2012. Urban water sector performance in Africa: a step-wise bias-corrected efficiency and effectiveness analysis. Util. Policy 22, 31–40.

Medal, A., Sala, R., 2009. A methodology for the selection of tolerances in the analysis of efficiency with DEA. In: Bernal, J.J., Sala, R. (Eds.), Aspectos Matematicos, Estadisticos e Informaticos. Universidad Politécnica de Cartagena, pp. 2009 (In Spanish).

Medal, A., 2010. Efficiency analysis of the Spanish port system: structure, evolution and perspectives. PhD Thesis. University of Valencia, Spain.

Molinos-Senante, M., Sala-Garrido, R., 2015. The impact of privatization approaches on the productivity growth of the water industry: a case study of Chile. Environ. Sci. Policy 50, 166–179.

Molinos-Senante, M., Maziotis, A., Sala-Garrido, R., 2014. The Luenberger productivity indicator in the water industry: an empirical analysis for England and Wales. Util. Policy 30, 18–28.

Molinos-Senante, M., Sala-Garrido, R., Lafuente, M., 2015a. The role of environmental variables on the efficiency of water and sewerage companies: a case study of Chile. Environ. Sci. Pollut. Res. 22 (13), 10242–10253.

Molinos-Senante, M., Hernández-Sancho, F., Sala-Garrido, R., 2015b. Comparing the dynamic performance of wastewater treatment systems: a metafrontier Malmquist productivity index approach. J. Environ. Manage. 161, 309–316.

Molinos-Senante, M., Hanley, N., Sala-Garrido, R., 2015c. Measuring the CO_2 shadow price for wastewater treatment: a directional distance function approach. Appl. Energy 144, 241–249.

Perez, F., Gomez, T., 2014. Multiobjective project portfolio selection with fuzzy constraints. Ann. Oper. Res. 1–23.

Romano, G., Guerrini, A., 2011. Measuring and comparing the efficiency of water utility companies: a data envelopment analysis approach. Util. Policy 19 (3), 202–209.

SISS (Superintendencia de Servicios Sanitarios), 2014. Water and Sewerage Services in 2014. Available from: http://www.siss.gob.cl/577/w3-article-11831.html (accessed 20.08.15.).

Saal, D.S., Parker, D., Weyman-Jones, T., 2007. Determining the contribution of technical change, efficiency change and scale change to productivity growth in the privatized English and Welsh water and sewerage industry: 1985–2000. J. Prod. Anal. 28 (1–2), 127–139.

Sala-Garrido, R., Hernández-Sancho, F., Molinos-Senante, M., 2012. Assessing the efficiency of wastewater treatment plants in an uncertain context: a DEA with tolerances approach. Environ. Sci. Policy 18, 34–44.

See, K.F., 2015. Exploring and analysing sources of technical efficiency in water supply services: some evidence from Southeast Asian public water utilities. Water Resour. Econ. 9, 23–44.

Sexton, T.R., Silkman, R.H., Hogan, A.J., 1986. Measuring Efficiency: An Assessment of Data Envelopment Analysis. In: Silkman, R.H. (Ed.), Jossey-Bass, SanFransisco (CA), pp. 73–105.

Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manage. Sci. 44 (1), 49–61.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. J. Econ. 136 (1), 31–64.

Torgersen, A.M., Foørsund, F.R., Kittelsen, S.A.C., 1996. Slack-adjusted efficiency measures and ranking of efficient units. J. Prod. Anal. 7 (4), 379–398.

Tupper, H.C., Resende, M., 2004. Efficiency and regulatory issues in the Brazilian water and sewerage sector: an empirical study. Util. Policy 12 (1), 29–40.

Zhu, J., 2015. Data Envelopment Analysis: A Handbook of Models and Methods. Springer..