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Eco-efficiency assessment of wastewater treatment plants using a weighted Russell directional distance model

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Improving the performance of wastewater treatment plants is essential to ensuring their long-term sustainability. Most of the previous studies on this topic have assessed the techno-economic efficiency of wastewater treatment plants and ignored the emission of greenhouse gases. For the first time, the weighted Russell directional distance model was applied to estimate the eco-efficiency of a sample of real wastewater treatment plants. Moreover, this approach allowed an inefficiency score to be obtained for each variable (cost factors, pollutant removal and greenhouse gases) involved in the model. Subsequently, a second stage of analysis was applied to identify factors influencing the previously computed inefficiency scores. The results illustrated that approximately half of the facilities assessed had significant room for improvement in their eco-efficiency. Moreover, the characteristics of over- and undersizing of the plants significantly affected their eco-efficiency. The methodology and results of this study are of great interest, not only for wastewater treatment plant managers and water authorities but also for citizens because there have been growing concerns regarding minimizing the ecological footprint in the urban water cycle.

1. Introduction

1.1. Background

Wastewater treatment is essential to protecting human health and environmental sustainability (IOC/UNESCO, 2011). Hence, several regulations concerning wastewater treatment have been developed such as the European Union Directive 91/271/ECC or the United States Clean Water Act. As a result, the number of wastewater treatment plants (WWTPs) worldwide has increased notably, and in developed regions, virtually the entire population (96%) has access to wastewater treatment services (WHO-UNICEF, 2014).

In this context, the performance assessment of WWTPs has gained the interest of WWTP managers and water authorities for improvement of the long term sustainability of these facilities (Piao et al., 2016). Moreover, comparative analysis (benchmarking) of WWTPs allows identification of the strengths and weaknesses of each plant (Molinos-Senante et al., 2014).

The urban water cycle is well-known to be the nexus of water-energy because water and wastewater facilities use between 30% and 60% of municipal government energy usage (US EPA, 2008). Focusing on WWTPs, energy consumption was approximately 15%–30% of the operation and maintenance costs of large WWTPs and 30%–40% at small WWTPs (WEF, 2009). Energy consumption involves indirect GHG emissions which are a major global environmental issue (Henriques and Catarino, in press; Li et al., 2016). The important role that the wastewater treatment industry could play in the reduction of GHG emissions has been already realized by

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a number of governments (Molinos-Senante et al., 2015a). Hence, it was essential to include GHG emissions in the efficiency assessment of WWTPs. However, to the best of our knowledge, only Lorenzo-Toja et al. (2015) has integrated emissions linked to energy use in the evaluation of the efficiency of a sample of WWTPs. Nevertheless, this author did not consider GHG emissions as undesirable outputs, instead integrating them as a negative environmental impacts through life cycle assessment.

The objectives of this paper were twofold. The first was to assess the eco-efficiency of a sample of WWTPs. In doing so, for the first time in the framework of WWTPs, a weighted Russell directional distance model (WRDDM), a non-radial DEA model that allowed an individual inefficiency score to be obtained for each input, desirable output and undesirable output at WWTP level, was applied. Hence, not only the total room for improvement of each WWTP's eco-efficiency but also the variables in which WWTP managers and water authorities should focus on to improve the performance of each facility were evaluated. The second objective of this paper was to explore the factors affecting the inefficiency scores of each previously computed input, desirable output and undesirable output. To illustrate the usefulness of the proposed methodological approach, an empirical application using data from real Spanish WWTPs was carried out.

This paper contributed to the current vein of literature in the field of WWTP performance assessment by computing, for the first time, the eco-efficiency of a sample of WWTPs by applying the WRDDM. It should be noted that although several previous studies' evaluations of the efficiency of WWTPs have used non-radial DEA models, none of them has integrated GHG emissions as undesirable outputs. Moreover, no studies have evaluated the efficiency of WWTPs to provide an individual score of inefficiency for each input, desirable output and undesirable output. Hence, this study provided a pioneering and novel approach to assess the eco-efficiency of WWTPs. Moreover, this study provided insights into the factors affecting individual inefficiency scores. We considered these topics to be very relevant and deserving of investigation.

From policy and managerial points of view, computing an inefficiency score for each variable involved into the evaluation model, rather than a total inefficiency (TI) score could provide WWTP managers and policy makers with vital information. The results obtained could enable them to identify the variables in which the WWTPs need to improve the most for its eco-efficiency. Moreover, the identification of some factors which significantly affect inefficiency scores is essential to improving the long-term sustainability of WWTPs. Thus WWTP managers and policy makers could implement different strategies in the planning and designing of new facilities. It should be noted that improving eco-efficiency of WWTPs not only involves increasing the pollutant removal efficiency and reducing GHG emissions but also decreasing operational and maintenance costs. Thus, improving the eco-efficiency of WWTPs is a potential way to reduce wastewater treatment tariffs. Hence, improving the eco-efficiency of WWTPs also has marked repercussions from a social perspective.

The paper unfolds as follows. Section 1.2 describes briefly the literature already published on the topic analyzed. Section 2 presents the methodology employed in the paper. Section 3 describes the sample data used in the case study and the variables considered. Section 4.1 presents the main findings regarding inefficiency scores while Section 4.2 explores the factors affecting inefficiency in WWTPs. The final section concludes.

1.2. Literature review

In the framework of wastewater treatment, a series of research studies have aimed at assessing the so called “techno-economic efficiency” of WWTPs (e.g., Guerrini et al., 2015; Molinos-Senante et al., 2016a; Tomei et al., 2016). This approach is based on consideration of the operational and maintenance costs of WWTPs as inputs, while the pollutants removed from wastewater as outputs (Castellet and Molinos-Senante, 2016). Using the benchmarking methodology of data envelopment analysis (DEA), these previous studies computed an efficiency score for each WWTP. The great advantage of this methodology is that it enables integration of multiple inputs and outputs into a single index (Guerrini et al., 2013), which provides synthesized information regarding the total performance of each facility evaluated.

Within the framework of DEA methodology, several models have been developed to evaluate the eco-efficiency of the analyzed firms by integrating CO_2 and other greenhouse gas (GHG) emissions into the efficiency assessment as undesirable outputs (Shabani et al., 2014; Yu et al., 2016). Accordingly, it was considered that the production process carried out by the firms not only produced desirable outputs but also undesirable outputs (Chung et al., 1997; Fujii and Managi, 2013). Hence, the efficiency assessment involved variables to maximize (i.e., desirable outputs) and variables to minimize (i.e., inputs and undesirable outputs).

From a methodological point of view, most of previous studies have evaluated the efficiency of WWTPs using radial DEA models. Among other issues, they were characterized by adjustment of all variables to efficiency targets by the same proportion (Fujii et al., 2015). Hence, they only provided a score of total efficiency which involves that information regarding the efficiency of specific inputs, and outputs integrated in the analysis could not be obtained (Zhou et al., 2012). To overcome this and other limitations,[1] non-radial DEA models were developed. They allowed for the degree of inefficiency for each input and/or output to be different (Yagi et al., 2015). In other words, an efficiency score for each input and output was obtained in addition to the total efficiency score. Moreover, they allowed the preferences of decision makers to be integrated into the efficiency assessment by assignment of different weights to different variables (Wei et al., 2015).

While from a theoretical point of view, it has been demonstrated that non-radial DEA models are more effective than radial DEA models in assessing the performance of firms (Skevas et al., 2012) in the framework of WWTPs, to the best of our knowledge, only three previous studies have applied a non-radial DEA approach. Firstly, Hernández-Sancho et al. (2011), Molinos-Senante et al. (2014) applied a non-radial DEA model known as the Russell measure, which allowed an efficiency score to be obtained for each input involved in the analysis. However, this measure did not provide information regarding specific performance in the generation of outputs. Secondly, Castellet and Molinos-Senante (2016) used the weighted slack-based measure to evaluate the efficiency of a sample of Spanish WWTPs. However, they not only applied this non-radial DEA model to obtain an efficiency score for each input and output but also to assign different weights to the outputs based on their environmental impacts. Moreover, it should be noted that none of these previous studies evaluated the eco-efficiency of the WWTPs, i.e., none of them integrated the GHG emissions of the WWTPs as undesirable outputs.

2. Methodology

To compute an efficiency score for each input and output (desirable and undesirable) of WWTPs, the WRDDM was applied. It was based on a directional distance function combined with a non-

[1] More information about the differences between radial and non-radial DEA models can be consulted at Cooper et al. (2011).

parametric DEA approach (Chen et al., 2010; Barros et al., 2012). It was considered that firms (WWTPs in this study) used a vector of inputs $x \in \Re_+^N$ to produce two types of vector of outputs: desirable outputs and undesirable outputs, which were denoted by the vector $y \in \Re_+^M$ and $b \in \Re_+^J$, respectively (Fujii et al., 2014).

The technology reference set was given by:

$$T = \{(x, y, b) : \ x \ can \ produce \ (y, b)\} \tag{1}$$

Formally, T satisfied the following assumptions (Chung et al., 1997): i) free disposability of desirable outputs (Eq. (2)), indicating that was possible to reduce the desirable outputs without reducing the undesirable outputs (Wei et al., 2015); ii) weak disposability of undesirable outputs (Eq. (3)), implying that it was feasible to reduce both desirable and undesirable outputs proportionally by θ (Färe et al., 1993). The presumption was that a firm had to undertake a certain length of cost to reduce undesirable outputs (Zhou et al., 2014) and; iii) desirable and undesirable outputs satisfied the null-jointness axiom (Eq. (4)), meaning that desirable outputs could not be produced without producing undesirable outputs (Bi et al., 2014).

$$(x, y, b) \in T \ \ and \ \ y' \leq y \rightarrow (x, y', \ b) \in T \tag{2}$$

$$if (x, y, b) \in T \ \ and \ 0 \leq \theta \leq 1, \ \ then (x, \theta y, \theta b) \in T \tag{3}$$

$$if \ (x, y, b) \in T \ \ and \ \ b = 0, \ \ then \ y = 0 \tag{4}$$

Within the framework of WWTPs, Molinos-Senante et al. (2015a) verified that these three assumptions were fulfilled when pollutants removed from wastewater were considered as desirable outputs and CO_2 emissions as undesirable output.

The directional distance function, seeking directional increase in the desirable outputs and decrease the undesirable outputs and inputs, could be defined by the following (Molinos-Senante et al., 2016a):

$$\overrightarrow{D}(x, y, b; g) = \sup\left\{\rho : \left(x + \rho g_x, y + \ \rho g_y, b + \rho g_b\right) \in T\right\} \tag{5}$$

where the vector $g = (g_x, g_y, g_b) = (-x, y, -b)$ determined the directions in which inputs, desirable outputs and undesirable outputs were scaled. The directional distance function gave both the expansion in desirable outputs and contraction in undesirable outputs and inputs. The value of ρ was the distance between the firm and the frontier. If one firm was on the frontier, then $\overrightarrow{D}(x, y, b; g) = 0$ and therefore, it was an efficient firm in comparison with the others. In contrast, if $\overrightarrow{D}(x, y, b; g) > 0$ then the firm was inefficient and have room for improving its performance. (Barros et al., 2012).

We supposed that there were $k = 1, \ldots, K$ firms (WWTPs in this study) and each one used inputs $x^k = \left(x_1^k, \ x_2^k, \ldots, x_N^k\right) \in \ \Re_+^N$ to produce desirable outputs $y^k = (y_1^k, \ y_2^k, \ldots, y_M^k) \in \ \Re_+^M$ and undesirable outputs $b^k = (b_1^k, \ b_2^k, \ldots, b_J^k) \in \ \Re_+^J$. Following Barros et al. (2012) and Fujii et al. (2014), the WRDDM for inefficiency calculation of firm k' could be described as follows:

$$\overrightarrow{D}\left(x^{k'}, \ y^{k'}, \ b^{k'}; g\right) = \rho^{k'} = \max \sum_{n=1}^{N} \varpi_n^{k'} \beta_n^{k'} + \sum_{m=1}^{M} \varpi_m^{k'} \beta_m^{k'} + \sum_{j=1}^{J} \varpi_j^{k'} \beta_j^{k'} \tag{6}$$

$s.t.$

$$\sum_{k=1}^{K} z^k y_m^k \geq y_m^{k'} + \beta_m^{k'} g_{ym} \quad m = 1, \ldots, M$$

$$\sum_{k=1}^{K} z^k b_j^k = b_j^{k'} + \beta_j^{k'} g_{bj} \quad j = 1, \ldots, J$$

$$\sum_{k=1}^{K} z^k x_n^k \leq x_n^{k'} + \beta_n^{k'} g_{xn} \quad n = 1, \ldots, N$$

$$\sum_{k=1}^{K} z^k = 1 \quad k = 1, \ldots, K$$

$$z^k \geq 0 \quad k = 1, \ldots, K$$

where $\beta_n^{k'}$, $\beta_m^{k'}$ and $\beta_j^{k'}$ were the individual inefficiency measures for each input x_n, each desirable output y_m and each undesirable output b_j, respectively. Accordingly, ρ^k was the weighted inefficiency score, also known as TI score because it took into account the inefficiency scores of all of the variables included in the assessment. z^k were the intensity variables to expand or shrink the individually observed activities of k to construct convex combinations of the observed inputs and outputs. The coefficients ϖ_n, ϖ_m, ϖ_j were the weights assigned to each input, desirable output and undesirable output, respectively, involved in the assessment. The coefficients were associated with the priorities given to the inputs and outputs (desirable and undesirable), and their sum was normalized to unity. Although there are methodologies to assign weights to a set of variables (Molinos-Senante et al., 2016b), in the present paper, it was considered that WWTPs had no priorities for the different inputs and outputs, i.e., assuming that all of them had the same importance. Accordingly, the ϖ_n, ϖ_m and ϖ_j were assigned based on the cardinal for each set of inputs, desirable outputs and undesirable outputs, respectively. Hence, ϖ_n, ϖ_m and ϖ_j were normalized as $1/N$, $1/M$ and $1/J$, respectively.

It should be noted that model (6) considered the convexity constraint. It involved the assumption that firms were operating under variable returns to scale (VRS). In the case of WWTPs, previous studies (Sala-Garrido et al., 2012; Mahmoudi et al., 2012; Mai et al., 2015) verified that outputs increased by more than the proportional change in inputs. Hence, from a managerial point of view, this meant that firms presented economies of scale.

One of the main advantages of the WRDDM over traditional DEA models was that it enabled an inefficiency score to be obtained for each input and output (desirable and undesirable) involved in the analysis. In other words, the WRDDM was able to determine each variable's contribution effect to inefficiency (Fujii et al., 2014). This issue is essential to WWTPs managers and water authorities for successfully improving the performance of the WWTPs. In addition to all limitations of DEA models (Garcia-Bernabeu et al., 2015), the WRDDM assumes that the increase of desirable output and the decrease of undesirable output follow a similar proportion, which is too strict in some cases (Chen and Zhang, 2014) but not in our empirical application.

2.1. Identification of factors affecting inefficiency scores

To identify some of the factors influencing inefficiency scores estimated by WRDDM, a second stage of analysis was conducted.

From a methodological point of view, previous studies have applied different approaches to identifying factors affecting efficiency scores (Da Cruz and Marques, 2014). Ordinary least squares (OLS) or Tobit regression methods have been widely applied (Guerrini et al., 2015). Under these approaches, the estimated efficiency scores were regressed on covariates which were considered to represent environmental variables (Molinos-Senante et al., 2014). Nonetheless, these procedures suffered from important methodological shortcomings (Badin et al., 2014). Hence, an alternative approach was introduced by Simar and Wilson (2002) which proposed a set of statistical tests based on bootstrap estimation procedure. Subsequently, Simar and Wilson (2007) used of the double-bootstrap methodology to audit the results attained using the OLS and Tobit regressions. In this context, De Witte and Marques (2010) and Carvalho and Marques (2011) used conditional order-m and order-α measures of efficiency. In spite of the advantages of this approach in identifying outliers, it also had some difficulties (Daraio and Simar, 2006). For example, the selection of the value for "m" was challenging because it affected the efficiency scores (Da Cruz and Marques, 2014).

Since inefficiency scores computed using DEA are based on a non-parametric method, it is natural to apply non-parametric statistics to provide a basis for statistical inference. Moreover, this approach does not require assumptions that the underlying distribution of efficiency scores is normal. Hence, factors affecting the performance of WWTPs were identified based on hypothesis test approach (Molinos-Senante et al., 2015b). Accordingly, firms (WWTPs in this study) were grouped based on certain factors or environmental variables that appeared to be related to inefficiency, and then tested if there were statistically significant differences between the group inefficiency scores. Taking into account the fact that inefficiency scores do not meet the assumptions of homoscedasticity and normality, non-parametric tests must be applied. Hence, the Mann-Whitney U and Kruskal-Wallis tests were applied to test the hypotheses. In particular, the hypotheses to be tested were as follows:

H0. The K samples were derived from the same population.

H1. Some samples were derived from other populations.

Whether the p-value was smaller than or equal than 0.05, the null hypothesis could be rejected. In other words, it could be considered that differences in inefficiency scores among the groups of WWTPs were different, at a 95% significance level (Tsagarakis, 2013).

3. Data and variables

The samples used in this empirical application consisted of 30 Spanish WWTPs; the information corresponded to the year 2014. All 30 of the facilities were operated by the same partnership, which involved the provincial council and the local council where each WWTP was located. Hence, it was a purely public partnership. From a technical point of view, all WWTPs assessed in this study removed suspended solids (SS) and organic matter using conventional secondary treatment without specific processes for nutrient removal. Nevertheless, it should be noted that the WWTPs had different secondary treatments, such as activated sludge, rotating biological contactors, and trickling filters.

Selection of the output (desirable and undesirable) and input variables included in facility performance assessment is always a challenging task, primarily depending on the criteria of the analyst and the availability of reliable information. However, within the framework of WWTPs, there is a wide consensus in the variables that must be considered in efficiency evaluation studies. Regarding desirable outputs, as Lorenzo-Toja et al. (2015) stated, they must summarise the function of the WWTP. Accordingly, as in several previous studies (e.g., Sala-Garrido et al., 2011; Molinos-Senante et al., 2014), the two main pollutants removed from wastewater, SS and organic matter (measured as chemical oxygen demand (COD)), constituted the desirable outputs. Both pollutants were expressed in kilograms per year in order to better integrate influent and effluent characteristics into the assessment (Carvalho and Marques, 2014). Four inputs were involved in the assessment namely: (i) staff costs which reflects wages, social security charges, taxes and social insurance; (ii) water management costs that include the costs associated with waste and sludge management; (iii) maintenance costs that include equipment and machinery maintenance and replacement and (iv) other costs which include the costs of the reagents required for wastewater and sludge treatment, laboratory costs and office supplies. All were expressed in € per year.

To select the undesirable output, the nexus water-energy was considered. The energy consumed by WWTPs has grown considerably in recent years as a result of increased wastewater treated and because of the implementation of new processes aimed at achieving larger effluent quality (Gu et al., 2016). Hence, GHG emissions, expressed in kilograms of CO_2 equivalent, were considered to be undesirable outputs. Following a life cycle assessment approach (e.g., Benetto et al., 2009; Kyung et al., 2015; Hendrickson et al., 2015), indirect GHG emissions were quantified based on the energy demand of the WWTPs and the peninsular Spanish electrical production mix. Subsequently, by using a 100-year global warming potential coefficient, these GHG emissions were converted to CO_2 equivalent emissions (Molinos-Senante et al., 2015a). According the Spanish Institute for Energy Diversification and Saving (IDAE, 2014), GHG emissions per kWh of produced electricity averaged 0.372 Kilograms of CO_2 equivalent. It would be interesting to include in the assessment not only indirect GHG but also direct GHG emissions resulting from the biological processes carried out in the WWTPs. Unfortunately, due to their measurement complexity, this information was not available for none of the facilities evaluated.

According to the selection of the variables, WWTPs were considered to be firms that through use of inputs (operation and maintenance costs), removed COD and SS (which was a desirable output) but also emitted GHG (which was considered an undesirable output of the production process). Table 1 provides descriptive statistics for the variables used in this study.

4. Results and discussion

4.1. Inefficiency scores of WWTPs

The WRDDM was applied to obtain an inefficiency score for each variable considered in the assessment. Table 2 reports the disaggregated inefficiency scores for individual inputs and desirable and undesirable outputs and TI at WWTP levels. For ease of interpretation, values indicating efficiency in the use of inputs or in the generation of outputs (desirable and undesirable) are shaded as grey boxes. It illustrated that 14 out of the 30 WWTPs evaluated had an inefficiency score equal to 0. This finding meant that 47% of the assessed plants were efficient with regard to their operational and maintenance costs, the removal of pollutants and the emission of GHG. These 14 WWTPs comprised the benchmark of best practices because they comparatively had the best performance.

As reported in the methodology section, from policy and managerial points of view, one strongpoint of the WRDDM was that it enabled inefficiency scores for each variable involved in the efficiency assessment of WWTPs to be obtained. Regarding the use of

Table 1
Sample description.

	Inputs				Desirable outputs		Undesirable output
	Staff costs (€/year)	Waste management costs (€/year)	Maintenance costs (€/year)	Other costs (€/year)	Organic matter removed (Kg COD/year)	Suspended solids removed (Kg/year)	Greenhouse gas ($TnCO_{2equi.}$/year)
Average	13,679	1670	1845	4885	418	161	23.25
SD	11,313	1913	1855	1259	226	83	30.48
Minimum	1347	100	90	3346	82	30	0.40
Maximum	48,657	6704	5780	8169	1108	388	111.67

Table 2
Inefficiency scores of the 30 wastewater treatment plants for each input, desirable output and undesirable output and total inefficiency.

	Staff costs	Waste costs	Maintenance costs	Other costs	Average inputs	Organic matter	Suspended solids	Average desirable outputs	Greenhouse gases	Total inefficiency
WWTP1	0.898	0.906	0.598	0.192	0.648	0.742	0.020	0.381	0.900	0.643
WWTP2	0.826	0.917	0.506	0.102	0.587	2.597	1.522	2.060	0.776	1.141
WWTP3	0.826	0.692	0.210	0.086	0.453	0.650	1.482	1.066	0.781	0.767
WWTP4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP5	0.929	0.774	0.609	0.189	0.625	0.949	0.000	0.475	0.906	0.669
WWTP6	0.877	0.931	0.599	0.397	0.701	0.000	0.000	0.000	0.892	0.531
WWTP7	0.935	0.370	0.876	0.387	0.642	3.270	1.669	2.469	0.882	1.331
WWTP8	0.807	0.416	0.938	0.076	0.559	0.000	0.199	0.099	0.888	0.515
WWTP9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP10	0.801	0.893	0.626	0.418	0.685	1.616	0.150	0.883	0.582	0.716
WWTP11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP12	0.824	0.729	0.978	0.104	0.659	0.290	1.704	0.997	0.806	0.820
WWTP13	0.520	0.801	0.482	0.167	0.492	0.630	0.322	0.476	0.000	0.323
WWTP14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP16	0.557	0.935	0.944	0.000	0.609	0.417	0.988	0.703	0.774	0.695
WWTP17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP21	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP22	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP23	0.701	0.166	0.882	0.258	0.502	0.105	0.522	0.313	0.930	0.582
WWTP24	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP25	0.559	0.166	0.752	0.040	0.379	1.006	0.189	0.597	0.401	0.459
WWTP26	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WWTP28	0.841	0.756	0.870	0.286	0.688	1.971	0.901	1.436	0.621	0.915
WWTP29	0.835	0.906	0.861	0.509	0.778	5.405	1.789	3.597	0.788	1.721
WWTP30	0.857	0.766	0.508	0.288	0.605	0.913	2.200	1.557	0.765	0.975
Average	0.420	0.371	0.375	0.117	0.320	0.685	0.455	0.570	0.390	0.427
SD	0.404	0.395	0.383	0.153	0.308	1.203	0.690	0.865	0.402	0.472
% efficient	46.7	46.7	46.7	50.0	46.7	53.3	53.3	50.0	50.0	46.7

inputs, Table 2 demonstrated that the same 14 WWTPs that were totally efficient were also efficient in the use of inputs. This finding meant that these WWTPs could not reduce their operational and maintenance costs while keeping up the removal of pollutants and down the emission of GHG. The average inefficiency score for inputs obtained considering all facilities was 0.320 indicating that on average WWTPs could reduce their operational and maintenance costs by 32%. Nevertheless, 14 WWTPs are efficient in the use of inputs. Hence, improvement efforts should be focused on the 16 inefficient facilities which represent 53% of the sample. In this context, it was found that the average inefficiency index was 0.601 meaning that inefficient WWTPs have a potential to save 60.1% of their operational and maintenance costs. This issue was especially prominent for staff costs and for specific WWTPs, such as WWTP1, WWTP10 and WWTP28.

Table 2 shows that 50% of the WWTPs evaluated were efficient in the removal of pollutants. However, independently analyzing each pollutant, the percentage of efficient plants increased to 53% because one facility was efficient in the removal of COD but not in the removal of SS and vice versa. Results indicate that inefficiency levels were on average 128% and 85% for the removal of COD and SS, respectively. This finding means that 47% of the facilities assessed might improve pollutants removal efficiency keeping the use of inputs and emission of GHG. Moreover, for all inefficient WWTPs, inefficiency scores were different for COD and SS removal. This information is essential to support the decision-making processes for WWTP managers in designing and implementing measures aimed to improve performance in the removal of specific pollutants from wastewater.

Finally, half of the facilities evaluated were considered efficient in the GHG emissions. In other words, they were efficient in the use of electrical energy. It should be noted that 14 out of the 15 efficient WWTPs, with regard to GHG emissions, were the ones that were totally efficient. Moreover, WWTP13 was identified as efficient for this specific variable while it was inefficient for the other variables involved in the study. The identification of energy efficient WWTPs is essential for reducing the carbon footprint of these facilities and for contributing to improvements in the sustainability of the urban water cycle.

If we look at the indicator of total inefficiency, it is illustrated that the average inefficiency for the 30 WWTPs evaluated was 42.7%. However, this figure increased up to 80.0% when only inefficient WWTPs were considered. Hence, results evidenced that 16 out of the 30 WWTPs assessed have a notable room for improving its performance. In order to further investigate factors that help to explain the differences in inefficiency scores among WWTPs, a second-stage analysis was carried out. Results are shown in Section 4.2.

4.2. Underlying factors

To gain a more realistic picture of WWTPs' inefficiency, evaluation of whether certain factors have effects on inefficiency scores was needed. In doing so, a two-step procedure, described in Section 2.1 was carried out. Because there was no formal theory as to what the determinants of the performance of WWTPs were, the variables included in this second stage were drawn from existing published literature (Marques, 2008; Carvalho and Marques, 2011; Hernández-Sancho et al., 2011), also taking the available statistical information into account.

It was assumed that inefficiency scores (TI and individual input and output inefficiency scores) may be affected by the following factors: (i) plant size, expressed as the volume of wastewater treated annually; (ii) characteristics of over- and undersized WWTPs, measured as the difference between real and designed flows; (iii) types of secondary treatment; (iv) technology used to dry the sewage sludge and; (v) age of the WWTP, defined as the number of years because the WWTP was build or refurbished. The average inefficiency scores for WWTPs grouped according these factors and also the category of each WWTP for all factors considered are shown as supplemental material.

4.2.1. WWTP size

The aim of this section was to test whether the evaluated WWTPs presented economies of scale and also to test whether large WWTPs were more efficient, not only from an economic point of view but also in light of the removal of pollutants and the emission of GHG. To this end, WWTPs were categorized into three groups based on the volume of wastewater treated annually: (i) less than 100,000 m^3/year (small WWTPs); (ii) between 100,000 and 400,000 m^3/year (medium WWTPs) and; (iii) more than 400,000 m^3/year (large WWTPs).

Fig. 1 shows the mean inefficiency scores for each input and output (desirable and undesirable) and TI. Surprisingly, for all variables considered, small WWTPs were more efficient than medium and large plants. Actually, 6 out of the 14 efficient plants were small, i.e., treating less than 100,000 m^3 of wastewater per year. It should be noted that only 1 out of the 6 large WWTPs was identified as totally efficient. The Kruskall-Wallis test (Table 3) allowed us to verify that differences in inefficiency scores between the three groups of WWTPs were significant for staff costs, other costs, and COD removal.

Regarding inefficiency for COD removal, large WWTPs exhibit the highest average score. This result is associated mainly to the poor performance of the WWTP7 and WWTP29 in the removal efficiency of COD. The concentration of COD in the effluent for both WWTPs fulfills the normative limit. However, the concentration of COD in the influent is really low and therefore, the quantity (kilograms) of COD removed from wastewater is comparatively small. Hence, WWTP7 and WWTP29 are very inefficient for the output COD removed.

While previous studies (Hernández-Sancho et al., 2011; Tsagarakis, 2013; Molinos-Senante et al., 2014) illustrated that WWTPs were affected by economies of scale; it should be

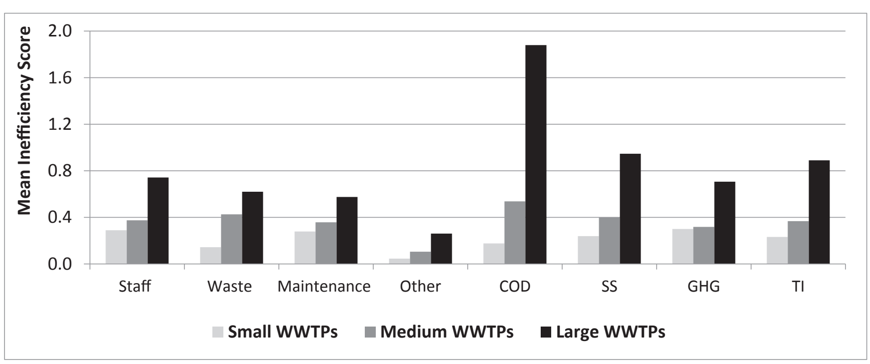

Fig. 1. Average inefficiency scores for small, medium and large WWTPs.

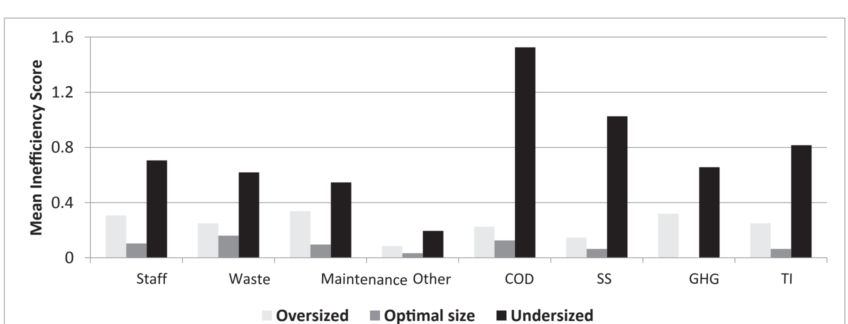

Fig. 2. Average inefficiency scores for oversized, optimal size and undersized WWTPs.

Table 3
p-value of the Kruskall-Wallis tests for WWTPs grouped based on several factors.

Factors	Staff	Waste	Maintenance	Other	COD	SS	GHG	TI
WWTP size	0.016	0.092	0.437	0.046	0.038	0.297	0.095	0.054
Over- and undersized	0.008	0.007	0.008	0.032	0.006	0.018	0.015	0.020
Secondary treatment	0.035	0.427	0.045	0.169	0.044	0.060	0.020	0.046
Technology to dry sewage sludge	0.050	0.079	0.324	0.014	0.147	0.567	0.030	0.072
WWTP age	0.965	0.790	0.476	0.859	0.824	0.919	0.625	0.965

highlighted that the 30 facilities analyzed in this study were operated by a partnership between the local and provincial councils. Hence, some of the small WWTPs shared staff and other costs (analytics and reagents), demonstrating “indirect” economies of scale, though they are not directly quantified.

From a policy perspective, this result evidences that operational and maintenance costs of WWTPs not depend only on its capacity but also on its management. Thus, to reduce operational costs a relative common practice is to construct large WWTPs that treat the wastewater from several towns. However, sometimes this strategy cannot be applied due to social, technological and environmental constraints (Libralato et al., 2012). In this context, an alternative to centralized WWTPs might be decentralized WWTPs but operated and managed by a common entity.

4.2.2. Characteristics of over- and undersized WWTPs

WWTPs have a long lifespan and therefore, the planning and design of these facilities is subject to uncertainty (Rajendran et al., 2014). Moreover, because of their location, some WWTPs are affected by seasonal changes in the flow of wastewater treated. Both issues lead to over- and undersized WWTPs. Usually, oversized plants involve unnecessary operational costs while undersized plants may have operational problems regarding efficiency of pollutant removal (Molinos-Senante et al., 2016a). In this context, it was considered that plants were over- or undersized when the percentage difference between the real and designed flows was smaller or larger than 10%, respectively (Sala-Garrido et al., 2012). According this criterion, the 30 WWTPs evaluated were grouped into three categories: (i) oversized WWTPs; (ii) optimally sized WWTPs and; (iii) undersized WWTPs.

As expected, both oversized and undersized WWTPs presented mean inefficiency scores larger than WWTPs whose real flow was pretty similar to designed flow (Fig. 2). In particular, 4 out of the 5 plants categorized as optimally sized WWTPs were totally efficient, i.e., were efficient in the use of all inputs, in the removal of pollutants, and in the emission of GHG. Moreover, the Kruskall-Wallis test (Table 3) led us to reject the hypothesis of equality of means for all scores of inefficiency, with 95% significance, based on the characteristics of oversize and undersize as explanatory variables. These results highlighted the importance of the design phase not only for minimizing the operational and maintenance costs of a WWTP over its life but also for maximizing its performance in the removal of pollutants and in GHG emission.

4.2.3. Type of secondary treatment

From a methodological point of view, certain technologies were more appropriate than others for small communities (Salas et al., 2011). The WWTPs analyzed presented three types of technology as secondary treatments, namely: (i) activated sludge; (ii) rotating biological contactors (biodisks) and; (iii) trickling filters. Because of the inherent characteristics of these three technologies, it might be expected that only large[2] plants had activated sludge. However, 5 out of the 10 small plants treated wastewater using activated sludge process. By contrast, 1 out of the 6 large WWTPs presented rotating biological contactors and another plant had trickling filters as a secondary treatment. Hence, for the sample of WWTPs evaluated in this study, there was no direct correlation between size and secondary treatment technology.

Fig. 3 shows that for all variables considered, plants using biodisks were more efficient than WWTPs using activated sludge or trickling filters as secondary treatments. This result was consistent with the conclusions drawn by Sala-Garrido et al. (2011), who compared the efficiency of several secondary treatments using the metafrontier concept. Regarding operational and maintenance costs, WWTPs using activated sludge were the most inefficient, with statistically significant differences in staff and maintenance costs. This meant that plants using biodisks had significantly lower staff and maintenance costs than WWTPs with activated sludge and trickling filters as secondary treatments. The Kruskall-Wallis test (Table 3) results also allowed us to reject the null hypothesis for GHG emissions. This finding revealed that WWTPs with biodisks had lower carbon footprints than plants using activated sludge or trickling filters. Within the current framework of climate change and incessant increase in electrical energy costs, it is essential to design WWTPs that minimize the use of energy, contributing to improvements in the sustainability of the WWTPs and of the urban water cycle.

4.2.4. Technology to dry sewage sludge

Wastewater treatment processes involve the generation of sewage sludge that must be managed adequately to prevent negative environmental impacts. Hence, the possible relationship between inefficiency scores and processes to dry sewage sludge was also investigated. In doing so, WWTPs were grouped into three groups: (i) WWTPs using centrifuges; (ii) WWTPs with drying beds; and (iii) WWTPs without a sludge drying process.

Regarding the use of inputs, Fig. 4 illustrates that facilities with drying beds were the most efficient in staff, waste and other costs, while for maintenance costs, plants which did not dry the sewage sludge had the highest efficiency. It should be noted that the inefficiency differences observed between the three groups of WWTPs were statistically significant only for staff and other costs (Table 3). Despite that drying beds demand more staff than centrifuges to operate them, the average inefficiency score was larger for WWTPs with centrifuges than for WWTPs with drying beds. It might be because 10 out of 14 total efficient WWTPs have drying beds to dry sewage sludge. Hence, the superior performance of these WWTPs in the management of all resources including staff balanced out the higher staff costs associated to drying beds. By contrast, because the removal of pollutants from wastewater was not related with the sewage sludge processes, the inefficiency differences between the three groups of WWTPs were not statistically significant (see Fig. 5).

Molinos-Senante et al. (2015a) concluded that the technology used to treat the sewage sludge significantly affects the energy consumption of WWTPs. The Kruskall-Wallis test results verified

[2] The categorization of the WWTPs as large or small was based on the criteria defined on Section 4.2.1.

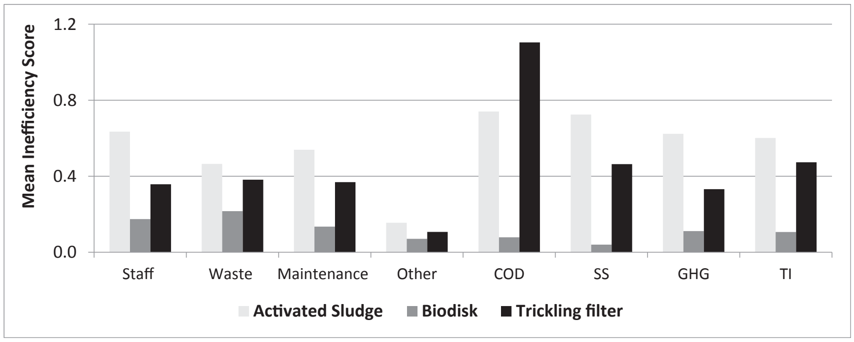

Fig. 3. Average inefficiency scores for WWTPs grouped based on its secondary treatment.

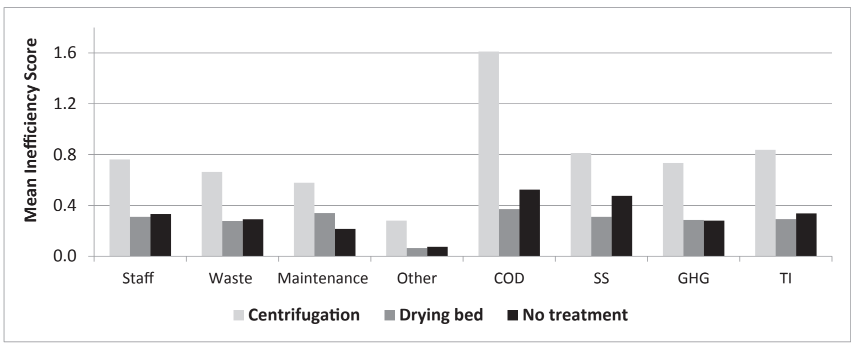

Fig. 4. Average inefficiency scores for WWTPs grouped based on its technology to dry sewage sludge.

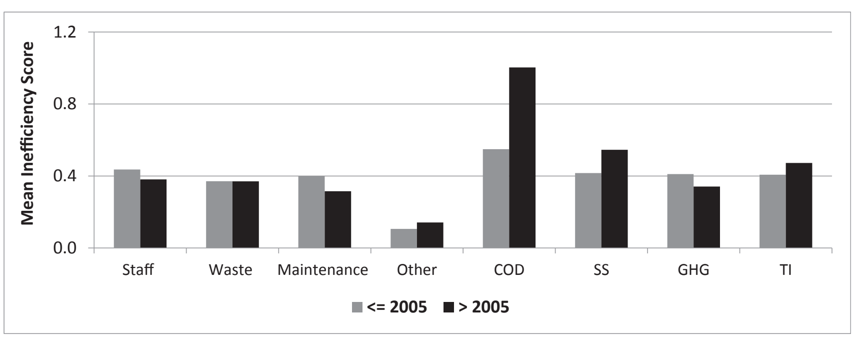

Fig. 5. Average inefficiency scores for WWTPs grouped based on its age.

this conclusion because Table 3 illustrated that the inefficiency scores were statistically significant for the emission of GHG. This finding meant that WWTPs which dried the sewage sludge with centrifuges consumed significantly more energy than plants which used drying beds. This issue is relevant to small WWTPs, where space is usually not a limitation, for implementation of natural processes that are much less energy demanding and therefore, more sustainable in the long term.

4.2.5. *Age of the WWTPs*

Finally, whether the age of the WWTPs affected its inefficiency was evaluated. Taking into account the fact that the oldest plant was built in 2000 while the newest one in 2012 and that 14 out of the 30 WWTPs analyzed were built in 2005, the sample data were split into two groups: (i) WWTPs built in or before 2005 and (ii) WWTPs built after 2005.

Previous studies (Hernández-Sancho et al., 2011; Molinos-Senante et al., 2014) showed evidence that the age of the plant was not a determining factor for its inputs and total efficiency. The results from the analyses carried out in this study allowed us to extend these conclusions to the desirable and undesirable outputs. In other words, Table 3 illustrates that inefficiency scores regarding pollutant removal and GHG emissions were not statistically significant. This finding provided valuable information to WWTPs' managers because it illustrated that the age of the plant was unrelated to inefficiency scores. This meant that proper maintenance is vital to extend the useful life of the facilities.

The assessment performed in the second stage of the inefficiency assessment illustrated the importance of decomposing TI in the individual scores. It was identified that the characteristics of over- and undersize of WWTPs had a significant impact on the inefficiency scores of their operational and maintenance costs as well as of the pollutant removal efficiency and GHG emissions. This issue is essential to improving the sustainability of the WWTPs from a holistic point of view, i.e., integrating economic, technical and environmental points of view. By contrast, the age of the plants did not affect their inefficiency scores. Thus, for both inputs and outputs, the differences in the inefficiency scores between the newest and the oldest facilities were not statistically significant.

Special mention must be made of the staff costs due to their importance in the total operational and maintenance costs of the assessed WWTPs. In this context, it was illustrated that the size of the plant and the technologies to treat the wastewater and to dry the sewage sludge significantly influenced the inefficiency scores of staff costs. While these factors could not be immediately modified by the current WWTP managers, this information was highly useful for water authorities to design and plan future WWTPs because improvement in the long term sustainability of the WWTPs is essential to reducing their operational costs. In the current framework of climate change, there is a tremendous concern to reduce the overall carbon footprint of the urban water cycle and of WWTPs in particular. In this context, the second-stage analysis highlighted the importance of selecting proper technologies to treat the wastewater and to dry the sewage sludge. It was revealed that neither the wastewater or sewage lines of WWTPs significantly affected the inefficiency scores in relation to indirect GHG emissions.

5. Conclusions

In recent years, the performance assessment of WWTPs has garnered increasing interest because it can provide essential information for improvement of the long-term sustainability of these facilities. In this context, the water-energy nexus revealed the important role that the wastewater treatment industry might play in the reduction of GHG emissions. Hence, in the framework of sustainability, assessing the eco-efficiency of WWTPs is fundamental for sound decision making.

Within the framework of WWTPs, eco-efficiency is a multidimensional issue because it integrates cost items, pollutants removal efficiency and GHG. Hence, DEA was an excellent methodological approach to evaluate the eco-efficiency of WWTPs because it allowed integration of multiple variables into an index of eco-efficiency. Within the DEA approach, there were several models which might be applied to compute efficiency scores, although not all of them are equally effective and reliable. In this context, for the first time, WRDDM was applied to estimate the eco-efficiency of a sample of real WWTPs. The great advantages of the WRDDM were as follows: (i) it allowed an inefficiency score to be obtained for each variable involved in the model in addition to the total inefficiency score and (ii) it allowed integration of the preference of decision makers into the eco-efficiency assessment, by assigning different weights to different variables.

To improve the eco-efficiency of the WWTPs, additional information on the performance scopes was needed. Hence, in this study, a second stage of analysis was carried out to explore factors and environmental variables influencing efficiency scores.

To illustrate the usefulness of the methodological approach proposed, an empirical application was developed which focused on a sample of 30 real Spanish WWTPs. The main findings of this study could be summarized as follows: (i) half of the WWTPs had significant room to improve their eco-efficiency; (ii) some plants were efficient regarding pollutant removal or GHG emissions but were not totally eco-efficient; (iii) average inefficiency scores revealed that the largest room to improve total eco-efficiency was linked to pollutant removal efficiency; (iv) the characteristics of over- and undersize significantly affected all individual inefficiency scores and total eco-efficiency of the WWTPs; (v) the age of the plants did not affect their eco-efficiency and; (vi) both the technology used to treat the water and the sewage sludge affect the efficiency of staff costs.

From a policy perspective, the findings of this study are of great interest for WWTP managers and wastewater authorities. First, WWTPs could improve their eco-efficiency by reducing their operational and maintenance costs and GHG emissions or by increasing their pollutant removal efficiency. The assessment of the eco-efficiency at plant level allowed each WWTP to identify the variables which acted specifically to improve its eco-efficiency. Second, the benchmarking process carried out in this study allowed wastewater authorities to identify the plants that could serve as reference for establishing future standards in the eco-efficiency framework. Third, wastewater authorities should provide incentives to WWTP companies to implement better operational practices for improvement of their eco-efficiency. These practices would involve positive effects, not only for WWTP operators but also for the citizens who pay for wastewater treatment services.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2016.07.057.

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