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Research article

Measuring the eco-efficiency of wastewater treatment plants under data uncertainty

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ABSTRACT

Eco-efficiency assessment is a useful tool for improving the sustainability of wastewater treatment plants (WWTPs). However, it is a complex task that requires the integration of several performance indicators into a single index. Data envelopment analysis (DEA) is established as a highly effective methodology for achieving this as it permits the integration of the service value, resource consumption and environmental impact variables as the desirable outputs, inputs and undesirable outputs, respectively. However, traditional DEA models omit uncertainties in the data that are likely to result in biased conclusions. This study pioneers the assessment of the eco-efficiency of WWTPs while accounting for the data uncertainty and integrating the greenhouse gas emissions as an undesirable output. The DEA-tolerance model was applied to compute the eco-efficiency scores for 729 scenarios for each facility tested for identifying the best- and worst-case scenarios. The WWTPs were also ranked based on their eco-efficiency scores. The results demonstrated the importance of integrating data uncertainty in eco-efficiency assessments; the performances of the WWTPs change notably based on the evaluated set of scenarios. The proposed methodological approach provides a reliable and robust framework for supporting decision-making processes.

1. Introduction

The United Nations Industrial Development Organization has identified eco-efficiency as a major strategic element for its work on sustainable development (UNIDO, 2012). Schaltegger and Sturm (1989) pioneered the definition of eco-efficiency as the ratio between the value added and environmental impact. Hence, in the term 'eco-efficiency', the prefix 'eco' represents both the ecological and economic performance (Yin et al., 2014). That is, eco-efficiency entails producing more goods and services with fewer resources and with lesser environmental impact (Koskela and Vehmas, 2012).

Eco-efficiency has been popularized as a management philosophy that encourages companies to balance their environmental and economic performances by promoting innovation, growth and competitiveness (WBCSD, 2000). Therefore, several studies have been conducted with the aim of evaluating the eco-efficiency of different sectors including the water and sanitation industry (Caiado et al., 2017). In this context, wastewater treatment plants (WWTPs) are a special type of productive unit that use resources (energy and materials) to remove pollutants from wastewater and discharge the treated water into the environment (Ren and Liang, 2017). Thus, according to the most widely used definition of eco-efficiency, which is the ratio between the value of products or services and the environmental impacts and resources consumption, eco-efficiency of WWTPs entails the removal of more pollutants from wastewater by incurring less economic costs and emitting fewer greenhouse gases (GHG). The capability to quantify the eco-efficiency of WWTPs is essential to determining successes, identifying and tracking trends, prioritizing actions and identifying areas for improvement (Molinos-Senante et al., 2016a). The achievement of Goal 6 of the Sustainable Development Goals of the

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2030 Agenda adopted by the United Nations (ensure access to water and sanitation for all) will involve a notable increase in the number of operational WWTPs worldwide. Thus, there is an increasing need to assess the eco-efficiency of WWTPs to improve their sustainability (Dong et al., 2017).

Eco-efficiency is a multidisciplinary concept, and therefore complicated to assess as it requires a holistic approach that integrates several performance indicators into a single index (Fan et al., 2017; Godoy-Duran et al., 2017). A few studies evaluating the eco-efficiency of WWTPs employed life-cycle assessment (LCA) (Lorenzo-Toja et al., 2015; Opher and Friedler, 2016; Zepon Tarpani and Azapagic, 2018) as it is a useful tool for evaluating the environmental performance of WWTPs (McNamara et al., 2016). However, in the specific context of eco-efficiency estimation, LCA has two main limitations. Firstly, it does not consider economic variables and therefore, does not integrate the economic dimension essential for eco-efficiency evaluation (Richa et al., 2017). Secondly, the applicability of LCA is generally limited by the requirement for a large amount of data (Curran, 2013). An alternative methodological approach employed to evaluate the eco-efficiency of WWTPs is data envelopment analysis (DEA) (Mai et al., 2015; Castellet and Molinos-Senante, 2016; Guerrini et al., 2017; Gómez et al., 2017). It integrates different sets of performance indicators—economic and environmental—within an organizational production process (Lahouel, 2016). In the context of assessing the eco-efficiency of WWTPs, Dong et al. (2017) reported that DEA is superior to LCA.

In the framework of eco-efficiency analysis, DEA presents an additional and fundamental advantage: it enables the integration of environmental impacts as undesirable outputs in the assessment. The significant advantage of this approach is that the holistically computed eco-efficiency score integrates the three dimensions of eco-efficiency: i) service value (desirable outputs), ii) resource consumption (inputs) and iii) environmental impacts (undesirable outputs) (Ji, 2013). Numerous studies have integrated environmental impacts as undesirable outputs in the eco-efficiency assessments of several types of productive units (e.g., Oggioni et al., 2011; Robaina-Alves et al., 2015; Xu et al., 2017).

Notwithstanding the fact that this is a significant methodological advantage, to our knowledge, only Molinos-Senante et al. (2016b) considered GHG emissions from WWTPs as an undesirable output while evaluating their eco-efficiency. Other studies, such as Hernández-Sancho et al. (2011), Sala-Garrido et al. (2012), and Gómez et al. (2017) evaluated the efficiency of WWTPs while completely omitting their environmental impacts. Thus, in a strictly rigorous sense, they evaluated the economic efficiency, rather than the eco-efficiency, of WWTPs. Recently, Dong et al. (2017) employed the DEA approach to assess the eco-efficiency of a sample of Chinese WWTPs while also taking GHG emissions into consideration. However, these authors integrate the environmental impact as an input rather than an undesirable output, which contradicts the assumptions of production theory (Färe et al., 1989). Section 2.1 discusses this issue further.

However, the positive features of DEA do not exempt it from limitations in terms of eco-efficiency assessments. DEA is a deterministic method and therefore cannot address imprecise data or provide information about uncertainty (Kao and Liu, 2014). The role of uncertainty is essential because the conclusions derived from eco-efficiency analyses are highly sensitive to errors in data (Bhardwaj et al., 2018). To overcome this problem and take uncertainty into account, several extensions to the traditional DEA models have been proposed, such as Monte Carlo simulation (Cordero et al., 2009), the α-level based approach (Carvalho and Marques, 2016), chance constraint (Momeni and Farzipoor Saen, 2012), bootstrapping (Simar and Wilson, 2007), fuzzy ranking (Han et al., 2015) and DEA-tolerance (Bonilla et al., 2004). Each of these methodological approaches exhibits advantages and shortcomings. However, Bonilla et al. (2004) demonstrated that the DEA-tolerance method is simpler and faster than the bootstrapping approach and provides similar results. Moreover, Dong et al. (2017) noted that the DEA-tolerance approach is less subjective than the fuzzy approach as it does not require the fuzzy sets of variables to be defined for all decision-making units. Furthermore, the DEA-tolerance approach can be combined with the system of indicators proposed by Boscá et al. (2011) that permits units to be ranked in an uncertain context. This is highly noteworthy in the framework of WWTPs because water and sanitation are regulated industries, wherein water tariffs are generally set based on benchmarking processes (price cap regulation), in numerous countries.

The DEA-tolerance approach has been successfully applied by Sala-Garrido et al. (2012) and Dong et al. (2017) to assess the eco-efficiency of WWTPs. However, the model employed by both studies involved only inputs and desirable outputs while omitting undesirable outputs. As previously mentioned, in eco-efficiency assessments, it is fundamental to integrate the environmental impacts as undesirable outputs, as they are jointly produced with the desirable outputs, although they must be minimized. Otherwise, the eco-efficiency scores estimated do not completely capture the holistic nature of the eco-efficiency concept based on service value, resource consumption and environmental impacts (Zhang et al., 2008).

The objective of this study was to evaluate the eco-efficiency of a sample of WWTPs while accounting for uncertainty. In achieving this, a DEA-tolerance model integrating GHG emissions as undesirable outputs was applied for the first time. The integration of data uncertainty in DEA models enabled the computation of the eco-efficiency scores for 729 scenarios and the identification and evaluation of the best- and worst-case scenarios for each facility (the scenarios are described in section 2.2). It reduces the uncertainty in eco-efficiency assessment. Moreover, WWTPs are benchmarked based on their scores using a robust approach that integrates uncertainty. Thus, this paper contributes to the current literature in the field of WWTP performance assessment. Moreover, it should be highlighted that to our knowledge, no prior studies applied the DEA-tolerance approach and included undesirable outputs for the eco-efficiency assessments of WWTPs or other productive sectors. Thus, we are also innovating in the field of performance assessment by providing a robust additional method for evaluating the eco-efficiency of units by directly integrating environmental impacts and uncertainty. Beyond academics, the observations of this study are also effective from a policy perspective. An evaluation of the eco-efficiency of WWTPs is essential for developing policies and measures to promote sustainable wastewater treatment. Moreover, benchmarking the performances of WWTPs based on the eco-efficiency scores considering uncertainty provides a reliable and robust ranking of the WWTPs analysed. This is essential for the decision-making process.

2. Methodology

2.1. Data envelopment analysis with undesirable outputs

The DEA methodology was applied to evaluate the eco-efficiency of WWTPs. DEA is a non-parametric method based on linear programming that permits the construction of an efficient production frontier based on the inputs and outputs of the units evaluated (WWTPs in this case-study) (Cooper et al., 2007). The relative position between the units and the production possibility frontier is represented by an eco-efficiency index ranging from zero to one (Dong et al., 2017). A WWTP is considered to be eco-efficient if its index equals one because it implies that it is located on the efficient frontier. In contrast, an eco-efficiency lesser than one indicates that the efficiency of the WWTP is low and requires improvement (Gómez et al., 2017).

In the traditional DEA models proposed by Charnes et al. (1978) and Banker et al. (1984), performance indicators were categorized as inputs and desirable outputs, where the former are resources used to produce outputs and the latter are the products or value-added services (Lahouel, 2016). However, as noted in the seminal work of Koopmans (1951), the production process is also likely to generate undesirable outputs such as pollutants or waste. This is the concept underlying eco-efficiency, which has three goals: i) to increase the value of the service or good, ii) to optimize the use of resources and iii) to reduce the environmental impact (Robaina-Alves et al., 2015). Expressing these objectives in DEA terms, eco-efficiency assessments require the integration of performance indicators as inputs, desirable outputs and undesirable outputs (Monastyrenko, 2017).

Several models within the framework of the DEA method have been proposed to incorporate undesirable outputs in efficiency assessments (Charles et al., 2012). There are two main types of approaches, direct and indirect, to handle undesirable outputs in DEA models (Scheel, 2001). Indirect approaches are based on the transformation of the data corresponding to the undesirable outputs into inputs or desirable outputs (Pérez et al., 2017). However, several studies have demonstrated the limitations of these approaches. For example, Seiford and Zhu (2002) noted that treating undesirable outputs as inputs does not reflect the actual production process because the input–output structure that defines the production process is lost. Liu and Sharp (1999) and Färe and Grosskopf (2004) demonstrated that several transformations to handle undesirable outputs can produce adverse results. In contrast, direct approaches do not alter the undesirable outputs and rather integrate them in the DEA model with constraints (Wang et al., 2012). Several studies (Färe and Grosskopf, 2003, 2004; 2009; Sahoo et al., 2011) have established that treating undesirable outputs in their original forms is consistent with the physical laws and standard axioms of production theory. Hence, this study applies the latter methodological approach to compute the eco-efficiency of WWTPs.

Following previous studies (Marques et al., 2014; Guerrini et al., 2015; Molinos-Senante et al., 2016a), a DEA approach based on assumptions of variable returns to scale and minimization orientation including undesirable outputs (Wang et al., 2012) (Eq. (1)) was employed to compute an eco-efficiency index for each WWTP evaluated. The use of variable returns to scale implies that WWTP inputs are affected by economies of scale; that is, plants treating a larger volume of wastewater tend to be more efficient than smaller ones (Hernández-Sancho et al., 2011).

Given n WWTPs and that WWTP k $(k = 1,2...,n)$ has vector $x_k = (x_{1k}, x_{2k},...,x_{Mk})$ of M inputs, vector $y_k = (y_{1k}, y_{2k},...,y_{Sk})$ of S desirable outputs and vector $b_k = (b_{1k}, b_{2k}, ...,b_{Lk},)$ of L undesirable outputs, the eco-efficiency θ is obtained according to the DEA model assuming variable returns to scale by solving the following linear programming problem for each WWTP:

$$\begin{aligned} & Min\theta \\ & s.\ t. \\ & \textstyle\sum_{k=1}^{n} \lambda_k x_{ik} \leq \theta x_{ik_0} \quad 1 \leq i \leq M \\ & \textstyle\sum_{k=1}^{n} \lambda_k y_{rk} \geq y_{rk_0} \quad 1 \leq r \leq S \\ & \textstyle\sum_{k=1}^{n} \lambda_k b_{lk} = b_{lk_0} \quad 1 \leq l \leq L \\ & \textstyle\sum_{k=1}^{n} \lambda_k = 1 \end{aligned} \tag{1}$$

where λ_k is a vector of intensity. The measure of eco-efficiency θ is bounded between zero and one. A WWTP is considered eco-efficient if $\theta = 1$, whereas it is considered eco-inefficient if $0 \leq \theta < 1$.

2.2. Eco-efficiency assessment under uncertainty

The DEA model expressed by Eq. (1) does not permit stochastic variations in data because imprecise and uncertain information constrains DEA models. Classic DEA requires that the exact values of all the inputs and outputs (desirable and undesirable) be specified. However, these assumptions may not be true because certain data cannot be measured precisely in practice (Eslami et al., 2012) as uncertainty is inherent in data that are either collected from WWTPs or monitored. Moreover, for decision-makers, it is essential to take the fluctuations of WWTP performance into account in eco-efficiency assessments (Dong et al., 2017).

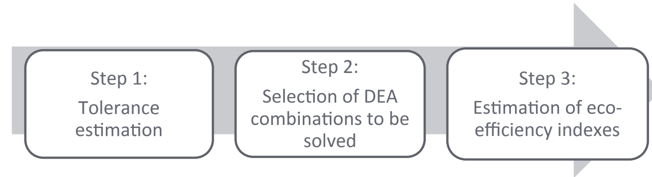

Fig. 1. Step to apply DEA-tolerance approach.
Source: Own elaboration from Molinos-Senante et al. (2016c).

The DEA-tolerance approach captures uncertainty by constructing intervals for data (Dyson and Shale, 2010). Thus, it provides information on the sensitivity of the eco-efficiency of WWTPs to changes in inputs and outputs (desirable and undesirable) by considering several scenarios for each WWTP. Fig. 1 shows the methodological steps carried out to compute eco-efficiency scores integrating uncertainty while employing the DEA-tolerance approach based on Molinos-Senante et al. (2016c).

Step 1: Tolerance estimation for each input, desirable output and undesirable output.

The definition of the tolerance values for inputs, desirable outputs and undesirable outputs was an essential step in applying the DEA-tolerance model. Following Medal and Sala (2009) and Sala-Garrido et al. (2012), tolerances were based on observations of historical series of each variable. This study set the tolerance level based on the annual averages of the inputs and outputs (desirable and undesirable) of WWTPs during 2014–2016 (another period can be selected depending on data availability). Symmetric and constant tolerances were also defined for each variable.

The tolerances defined are non-negative scalar values and express the positive and negative changes in the values of the inputs and outputs (desirable and undesirable) as follows:

$$\begin{aligned} & \text{Tolerance for inputs: } \alpha_{ik} = x_{ik} r_{ik} \\ & \text{Tolerance for desirable outputs: } \beta_{rk} = y_{rk} s_{rk} \\ & \text{Tolerance for undesirable outputs: } \gamma_{lk} = b_{lk} t_{lk} \end{aligned} \tag{2}$$

where r_{ik}, s_{rk} and t_{lk} are the percentages of deviation from the original values for the inputs, desirable outputs and undesirable outputs, respectively and fall in the range $[0 - 100]$.

According to the tolerance values defined, the values of the inputs and outputs should be within the following ranges:

$$\begin{aligned} & x_{ik} \in [x_{ik}(1 - r_{ik}), x_{ik}(1 + r_{ik})] \\ & y_{rk} \in [y_{rk}(1 - s_{rk}), y_{rk}(1 + s_{rk})] \\ & b_{lk} \in [b_{lk}(1 - y_{lk}), b_{lk}(1 + t_{lk})] \end{aligned} \tag{3}$$

Step 2: Selection of DEA combinations to be solved.

Equation (3) reveals the existence of a large set of feasible combinations of inputs, desirable outputs and undesirable outputs. This step involves the selection of the scenarios for which the eco-efficiency indexes are computed. Following Medal (2010), this case study simulated 729 scenarios for each facility, yielding the maximum (best case) and minimum (worst case) eco-efficiency index in addition to the mean value. It involves solving Eq. (1) 729 times for each WWTP because 3^6 $(= 729)$ scenarios were created for each WWTP. These corresponded to three situations, namely, (i) best case, (ii) worst case and (iii) original, with six feasible inputs and outputs, i.e., (1) inputs for the WWTP analysed, (2) desirable outputs for the WWTP analysed, (3) undesirable outputs for the WWTP analysed, (4) inputs for the remaining WWTPs, (5) desirable outputs for the remaining WWTPs and (6) undesirable outputs for the remaining WWTPs.

Thus, the following values are considered to evaluate the eco-efficiency of WWTP k_0 and its inputs, desirable outputs and undesirable outputs:

$$\begin{aligned}
&\text{Inputs of WWTP: } x_{ik_0}(1-r_{ik_0}),\ x_{ik_0},\ x_{ik_0}(1+r_{ik_0})\\
&\text{Desirable outputs of WWTP: } y_{rk_0}(1-s_{rk_0}),\ y_{rk_0},\ y_{rk_0}(1+s_{rk_0})\\
&\text{Undesirable outputs of WWTP: } b_{lk_0}(1-t_{lk_0}),\ b_{lk_0},\ b_{lk_0}(1+t_{lko})\\
&\text{Inputs of WWTP: } x_{ik}(1-r_{ik}),\ x_{ik},\ x_{ik}(1+r_{ik})\\
&\text{Desirable outputs of WWTP: } y_{rk}(1-s_{rk}),\ y_{rk},\ y_{rk}(1+s_{rk})\\
&\text{Undesirable outputs of WWTP: } b_{lk}(1-t_{lk}),\ b_{lk},\ b_{lk}(1+t_{lk})
\end{aligned} \quad (4)$$

Step 3: Estimating eco-efficiency indexes for each WWTP.

The 729 DEA combinations defined in Step 2 result in two extreme scenarios for each WWTP k_0: (i) the best-case scenario (the best for the WWTP evaluated, considering the lowest values for inputs and undesirable outputs and the highest values for desirable outputs) and (ii) the worst-case scenario (the opposite situation). The values of the inputs and the desirable and undesirable outputs for each scenario (where k_0 is the evaluated WWTP) are as follows:

$$\text{Best-case scenario:}\quad x_{ik}=\begin{cases}x_{ik_0}*(1-r_{ik_0})\\ x_{ik}*(1+r_{ik})\end{cases}\quad y_{rk}=\begin{cases}y_{rk_0}*(1+s_{rk_0})\\ y_{rk}*(1-s_{rk})\end{cases}\quad b_{lk}=\begin{cases}b_{lk_0}*(1-t_{lk_0})\\ b_{lk}*(1+t_{lk})\end{cases} \quad (5)$$

$$\text{Worst-case scenario:}\quad x_{ik}=\begin{cases}x_{ik_0}*(1+r_{ik_0})\\ x_{ik}*(1-r_{ik})\end{cases}\quad y_{rk}=\begin{cases}y_{rk_0}*(1-s_{rk_0})\\ y_{rk}*(1+s_{rk})\end{cases}\quad b_{lk}=\begin{cases}b_{lk_0}*(1+t_{lk_0})\\ b_{lk}*(1-t_{lk})\end{cases} \quad (6)$$

Under the best- and worst-case scenarios, the maximum and minimum eco-efficiency indexes, respectively, are obtained for each WWTP evaluated, permitting the uncertainty of the eco-efficiency assessment to be narrowed down.

2.3. Eco-efficiency and ranking of WWTPs

In a regulated industry such as urban water, one of the objectives of eco-efficiency evaluation is to benchmark the WWTPs analysed. Using the DEA approach alone, several WWTPs can be categorized as eco-efficient, and therefore, ranking them directly is not feasible. This limitation can be overcome using the DEA-tolerance estimation framework because it estimates the efficiency indexes for several scenarios. Thus, Boscá et al. (2011) proposed two indicators to rank WWTPs based on the number of times they are categorized as efficient. We modified those indicators to rank WWTPs based on their eco-efficiency, considering that our assessment involved 729 case scenarios rather than 81 since Boscá et al. (2011) only considered the desirable outputs and inputs.

The two eco-efficiency indicators for the k_0-th order WWTP are defined as follows:

$$R^1_{k_0}=\frac{e_{k_0}}{\tau_{k_0}} \quad (7)$$

$$R^2_{k_0}=\begin{cases}\dfrac{S_{k_0}-e_{k_0}}{\tau_{k_0}-e_{k_0}} & if\ \tau_{k_0}\neq e_{k_0}\\ 0 \quad if\ R^1_{k_0}=1\end{cases} \quad (8)$$

where e_{k_0} is the number of times that the eco-efficiency index of WWTP k_0 is equal to one; τ_{k_0} is equal to 729, the number of scenarios analysed for each WWTP and $S_{k_0}$is the sum of the eco-efficiency indexes of WWTP k_0.

$R^1_{k_0}$ is bounded between zero and one and denotes the proportion of times that WWTP k_0 is eco-efficient. A value of zero implies that WWTP k_0 was eco-inefficient in all the 729 scenarios evaluated. In contrast, when$R^1_{k_0}$equals one, the WWTP is eco-efficient in all the scenarios evaluated. Therefore, the higher the value of $R^1_{k_0}$is, the higher is the propensity of the WWTP to be eco-efficient (Sala-Garrido et al., 2012). The indicator $R^2_{k_0}$, also bounded between zero and one, is used to rank two WWTPs that have an identical value for the first indicator, $R^1_{k_0}$.

3. Sample description

The empirical application of this study is focused on evaluating the eco-efficiency of a sample of 30 Spanish WWTPs operated by the same public partnership. As one of the objectives of this study was to benchmark the eco-efficiency of the WWTPs, it was essential to compare homogeneous facilities, such as those designed to remove the same pollutants. The 30 plants evaluated remove suspended solids (SS) and organic matter using conventional secondary treatment and do not perform specific processes for nutrient (nitrogen and phosphorus) removal. The volume of wastewater treated by each of these facilities ranges between 22 000 m^3/y and 555 000 m^3/y; therefore, they are considered small plants (Lorenzo-Toja et al., 2015).

The selection of inputs, desirable outputs and undesirable outputs was based on previous studies that evaluated the eco-efficiency of WWTPs (Molinos-Senante et al., 2016b; Dong et al., 2017) and the broader concept of eco-efficiency (see Fig. 2 and Table 1). The inputs reflect the amount of resources consumed by the WWTPs. Therefore, they were represented by the operational and maintenance costs of the facilities (€/year) (Guerrini et al., 2015), which are grouped into the following four categories: i) staff costs, which include the salaries and social charges of the WWTP employees; ii) maintenance costs, which

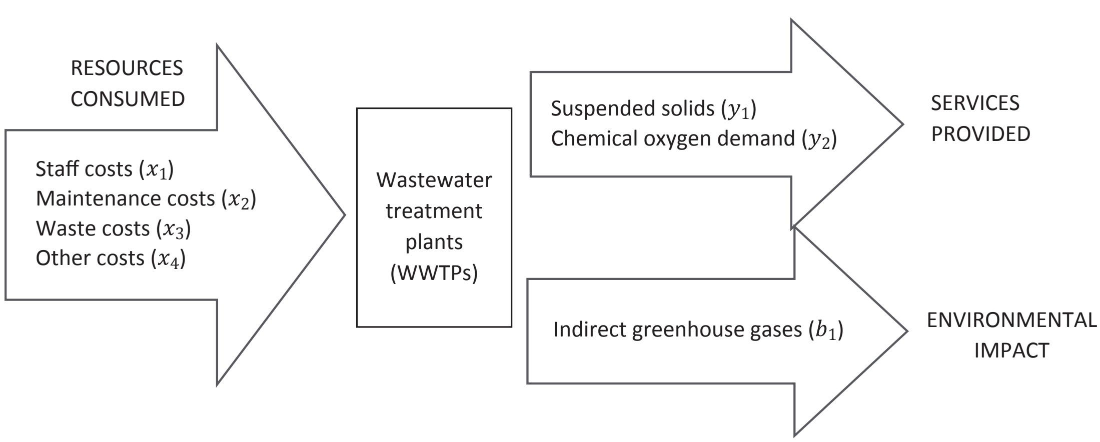

Fig. 2. Eco-efficiency modelling for wastewater treatment plants.

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 (Kg CO_2-eq/year)
Average	17167	2240	2000	3215	423	161	16029
SD	14198	2458	2078	1003	234	68	18156
Minimum	1691	7	73	2236	93	33	160
Maximum	61063	9733	10107	6663	1112	387	64475

include the equipment and machinery maintenance and replacement costs; iii) waste management costs, which include the costs related to waste and sludge management (not treatment) and iv) other costs (for reagents, the laboratory, office supplies, etc.). Notwithstanding the importance of energy costs among the operating costs of WWTPs, they were not considered as input in order to prevent double counting because energy consumption is a fundamental variable for estimating the indirect GHG emissions of each facility. Within the framework of eco-efficiency evaluation, desirable outputs refer to the value of the services provided (Ji, 2013). The main function of WWTPs is to reduce the negative impacts on water bodies by reducing the pollutants discharged into them. Taking into account the operational characteristics of the WWTPs assessed in this study, two desirable outputs were integrated in the DEA-tolerance model: the SS and the organic matter measured as chemical oxygen demand (COD). Both the variables were expressed in kg/y; therefore, the influent and effluent characteristics were integrated in the assessment. It should be noted that all the WWTPs satisfy the effluent quality requirements specified in the European Urban Wastewater Directive 91/271/EEC.

This paper pioneers the integration of environmental impacts as undesirable outputs in the eco-efficiency assessments of WWTPs. In particular, this study focused on the effects of WWTP operation on climate change. This was because in recent years, the amount of energy consumed by WWTPs increased owing both to an increase in the volume of wastewater treated and to newer and more stringent effluent quality regulations (Gu et al., 2017). The operation of WWTPs involves direct and indirect emissions of GHGs, mainly CO_2, N_2O and CH_4 (Meneses et al., 2015). The 30 WWTPs evaluated in this study do not remove nitrogen or monitor its concentration in their effluent. Therefore, notwithstanding the high global warming potential of N_2O compared to that of CO_2 (IPCC, 2014), it was not feasible to estimate the direct emissions of N_2O from these WWTPs. This is also the case with CH_4 because none of the facilities evaluated treat sludge anaerobically or monitor CH_4 emissions. Direct emissions of CO_2 consist mostly of biogenic carbon and therefore do not make an extra contribution to global warming (Wang, 2010). Thus, this study considered indirect GHG emissions (expressed as Kg CO_2-eq/y) as the undesirable output in the eco-efficiency evaluations of the WWTPs (Molinos-Senante et al., 2016b). The emissions were estimated based on the energy consumed by the facilities (kWh/y), the Spanish electrical production mix for 2016 and the coefficient of the 100-year global warming potential (308 g CO_2-eq/y per kWh of electricity produced).

4. Results and discussion

4.1. Eco-efficiency of WWTPs under uncertainty

To compute the eco-efficiency scores of the WWTPs for the 729 scenarios, the first step was to estimate the tolerance values for each variable integrated in the DEA-tolerance model (Fig. 1) . The tolerance values reflect the potential data uncertainty for each variable. Table 2 lists the values of symmetric tolerance estimated for the inputs (costs for staff, maintenance, and waste management, etc.), desirable outputs (COD and SS removed) and undesirable output (GHG emissions) expressed as a percentage of the original data.

The undesirable output presents the lowest tolerance value, which implies that this variable exhibits the lowest uncertainty in the WWTP eco-efficiency assessments. However, it should be noted that the data availability restrictions at the time of this study implied that only indirect GHG emissions (those related to energy consumption) were considered. The fact that the GHG emissions variable presents the lowest uncertainty highlights the importance that the managers of WWTPs accord to energy issues. In contrast, the inputs (the variables related to the operational and maintenance costs) exhibit the highest tolerance values. Of these, the highest variability (uncertainty) is observed in the maintenance costs. This illustrates that the economic efforts undertaken by the WWTPs vary significantly over time depending on the needs of the facilities. The two desirable outputs, the removal of SS and COD, exhibit similar moderate tolerance values. This is because they are only partially regulated by the WWTP operators as the concentration of pollutants in the influent depends on urban residents and the effluent must comply with environmental regulations (Directive 91/271/EEC).

The application of the DEA-tolerance model and inclusion of undesirable outputs generated 729 eco-efficiency scores for each WWTP under an equal number of likely scenarios. It yielded the range within which the eco-efficiency scores varied, thus narrowing the uncertainty in the eco-efficiency of each WWTP evaluated. To inspect the results more closely, the eco-efficiency scores of four specific groups were selected and are presented in Table 3: i) the 'original', which is the eco-efficiency score obtained using the original data, ii) the 'mean', which is the average eco-efficiency score of the 729 scenarios evaluated, iii) the 'maximum', which is the highest eco-efficiency score obtained and therefore represents the best-case scenario of the WWTPs assessed and iv) the 'minimum', which is the lowest eco-efficiency score obtained and therefore represents the worst-case scenario of the WWTPs assessed.

Based on the original data, the average eco-efficiency of the 30 WWTPs evaluated was 0.454, which indicates that the potential to save costs, reduce GHG emissions and improve the pollutant removal efficiency is 54.6%. Under the best-case scenario, the average maximum eco-efficiency score of the WWTPs could potentially attain 0.618, which implies a feasibility of improvement by approximately 38%. In contrast, under the worst-case scenario, the average minimum eco-efficiency score was 0.339, indicating a potential improvement of 66%. The average mean eco-efficiency score for the 729 scenarios evaluated was 0.482, which is very close to the average score using the original data. Table 3 illustrates that the eco-efficiency scores of the 30 WWTPs exhibit large standard deviations under the scenarios evaluated. For example, using the original data, the minimum eco-efficiency score was 0.037; this is very low as it indicates that this plant could improve its eco-efficiency by 96% compared to the most eco-efficient ones.

With regard to the WWTPs with the highest performances, Table 3 illustrates that eight out of 30 WWTPs (27%) were eco-efficient based on the original data, implying that they were located on the efficient frontier. Eight additional WWTPs could become eco-efficient, in the

Table 2
Tolerances for inputs, desirable outputs and undesirable output in %.

Staff costs	Waste management costs	Maintenance costs	Other costs	Organic matter removed	Suspended solids removed	Greenhouse gas
4.18	6.86	12.97	2.97	3.41	3.38	2.83

Table 3
Eco-efficiency scores of wastewater treatment plants (WWTPs) for 729 scenarios.

WWTP	Original	Mean	Maximum	Minimum	Amplitude (max-min) (%)
1	0.167	0.454	1.000	0.047	95.3
2	0.612	0.639	1.000	0.208	79.2
3	0.618	0.622	1.000	0.432	56.8
4	0.144	0.145	0.164	0.127	3.7
5	0.037	0.044	0.124	0.032	9.2
6	0.104	0.104	0.118	0.092	2.7
7	0.450	0.623	1.000	0.266	73.4
8	1.000	1.000	1.000	1.000	0.0
9	0.223	0.224	0.254	0.196	5.8
10	0.072	0.072	0.082	0.063	1.8
11	1.000	1.000	1.000	1.000	0.0
12	0.061	0.062	0.087	0.047	4.0
13	0.177	0.177	0.201	0.156	4.5
14	0.609	0.678	1.000	0.131	86.9
15	1.000	1.000	1.000	1.000	0.0
16	0.113	0.114	0.129	0.100	2.9
17	1.000	1.000	1.000	1.000	0.0
18	0.256	0.257	0.335	0.198	13.8
19	0.319	0.319	0.363	0.280	8.2
20	1.000	1.000	1.000	1.000	0.0
21	0.417	0.667	1.000	0.336	66.4
22	0.145	0.145	0.165	0.128	3.7
23	0.173	0.182	0.380	0.130	25.0
24	1.000	0.719	1.000	0.186	81.4
25	1.000	1.000	1.000	1.000	0.0
26	1.000	0.995	1.000	0.587	41.3
27	0.657	0.659	1.000	0.271	72.9
28	0.075	0.075	0.086	0.066	1.9
29	0.046	0.046	0.052	0.040	1.2
30	0.156	0.433	1.000	0.058	94.2
Mean	0.454	0.482	0.618	0.339	27.87
SD	0.378	0.363	0.422	0.357	35.34

best-case scenario, by increasing their pollutant removal efficiency or decreasing their operational and maintenance costs and GHG emissions to within the defined tolerance values. This demonstrates that in the most favourable scenario, 16 out of the 30 WWTPs (53%) are likely to be eco-efficient; however, the remaining facilities evaluated (47%) would not become eco-efficient even in the best-case scenario. In contrast, in the worst-case scenario 6 out of the 30 WWTPs (20%) were identified as eco-efficient, implying that two facilities that were considered eco-efficient based on the original data cease to be so in the pessimistic scenario. From a management perspective, these WWTPs should be vigilant as marginal changes in their performance could cause them to lose their eco-efficiency status. These results illustrate the importance of considering uncertainty in eco-efficiency assessments.

Fig. 3 illustrates the impact of data uncertainty on the estimation of the eco-efficiency of the WWTPs evaluated. It illustrates the variation intervals between the best and worst cases out of the 729 scenarios assessed as well as the mean values of the WWTP eco-efficiency scores. The different lengths of the bars indicate the stability of the eco-efficiency scores. That is, they denote the extent to which the uncertainties in the inputs, desirable outputs and undesirable output impact the eco-efficiency scores of each WWTP. A high amplitude reveals that there are large differences in scores between the best- and worst-case scenarios and that therefore, the data uncertainty exerts a large impact on the latter. In contrast, a low amplitude indicates that the eco-efficiency will change only minimally irrespective of variations (uncertainty) in the data.

Fig. 3 shows that six of the WWTPs are eco-efficient under the 729 scenarios evaluated. This indicates that the eco-efficiency of these plants is not impacted by uncertainties in data. Another group of WWTPs exhibit low variability in their eco-efficiency scores, which implies that their scores do not differ notably under either the best- or worst-case scenarios. Nevertheless, this group of WWTPs are characterized by their low eco-efficiency scores even in the former; for example, the eco-efficiency scores of WWTP 29 are 0.05 and 0.04 in the best- and worst-case scenarios, respectively. A third group of plants exhibited a large amplitude between their maximum and minimum eco-efficiency scores. These WWTPs can be considered highly 'sensitive' because uncertainty exerts a notable impact on their eco-efficiency scores. The extreme example is the WWTP1, whose eco-efficiency score ranges between a minimum of 0.04 in the least favourable and a maximum of 1.0 (eco-efficient) in the most favourable scenario of the WWTPs assessed.

From a management perspective, it is highly effective to compare the sensitivities of different facilities to data uncertainty when evaluating eco-efficiency. Thus, it is important to have accurate information on the performance indicators of the facilities, particularly if the eco-efficiency assessment serves benchmarking purposes for setting wastewater treatment tariffs, such as those that occur in price cap regulation approaches.

4.2. Ranking WWTPs based on eco-efficiency scores under uncertainty

The indicators R^1_{ko} and R^2_{ko} were computed to rank the WWTPs according to their eco-efficiencies (see Section 2.3). This approach enabled an accurate ranking of the WWTPs based on their scores for the 729 scenarios evaluated. The rankings are thus highly robust because they are based on numerous eco-efficiency estimations rather than a single estimate as is the case in traditional assessment. Table 4 shows the values of both the indicators for the WWTPs assessed.

Based on the R^1_{ko} indicator, it is evident that WWTPs 8, 11, 15, 17, 20 and 25 occupy the first position in the ranking as they are eco-efficient under all the 729 scenarios evaluated. It should also be noted that under the original data scenario, eight facilities were identified as eco-efficient. Thus, the inclusion of data uncertainty in the assessment generated a more accurate ranking of the WWTP based on eco-efficiency scores. A second group of WWTPs (1, 2, 3, 7, 14, 21, 24, 26, 27 and 30) were categorized as eco-efficient in a few of the scenarios evaluated. For example, R^1 for WWTP 27 was 0.444, implying that in 44.4% of the evaluations (324 scenarios), this facility was identified as eco-efficient. The other WWTPs have R^1_{ko} values equal to zero, indicating that they were identified as eco-inefficient in all the 729 scenarios.

The results of the R^2_{ko} indicator facilitate the ranking of the WWTPs that exhibit the same value of $R^1_{ko} \neq 1$. In this case study, the R^2_{ko} values helped rank WWTPs 21 and 27, 14 and 1 and 7 and 30 when each of the pairs exhibited identical R^1_{ko} values. Each of these WWTP pairs presented identical eco-efficiency scores when the original data was used to compute them; however, they performed differently under the worst-case scenario. Moreover, the R^2_{ko} indicator permitted the ranking of the WWTPs for which $R^1_{ko} = 0$; these were facilities that were not identified as eco-efficient even in the best-case scenario. Table 4 reveals that WWTP 19 occupies the highest position in this ranking of plants, whereas WWTP5 is identified as the less eco-efficient facility.

The hierarchical ranking of WWTPs is of significant interest for (waste) water regulators as it compares the eco-efficiency of WWTPs

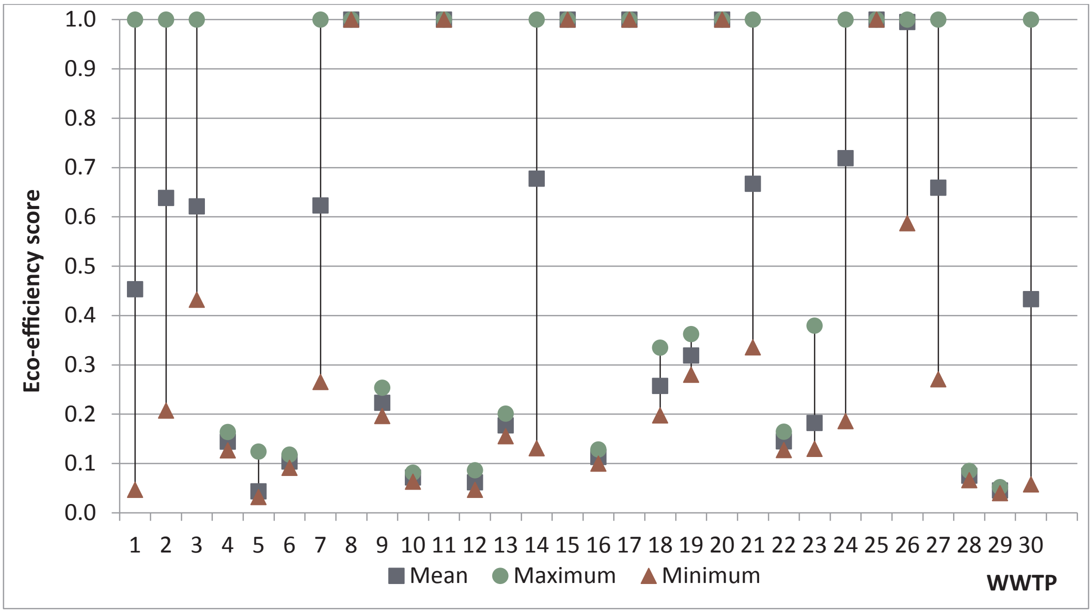

Fig. 3. Eco-efficiency scores of each wastewater treatment plant (WWTP) for 729 scenarios: mean, maximum and minimum scores.

Table 4
Ranking of wastewater treatment plants (WWTPs) based on eco-efficiency scores for 729 scenarios.

WWTP	R^1_{ko}	R^2_{ko}
8	1.000	–
11	1.000	–
15	1.000	–
17	1.000	–
20	1.000	–
25	1.000	–
26	0.988	0.624
24	0.630	0.242
21	0.444	0.401
27	0.444	0.387
14	0.383	0.478
1	0.383	0.115
7	0.358	0.413
30	0.358	0.117
2	0.169	0.566
3	0.012	0.617
19	0.000	0.319
18	0.000	0.257
9	0.000	0.224
23	0.000	0.182
13	0.000	0.177
22	0.000	0.145
4	0.000	0.145
16	0.000	0.114
6	0.000	0.104
28	0.000	0.075
10	0.000	0.072
12	0.000	0.062
29	0.000	0.046
5	0.000	0.044

addressing the same regulatory framework. Unlike traditional ranking systems, the integration of uncertainty in eco-efficiency assessment facilitates discrimination among WWTPs with similar performances. Moreover, Dong et al. (2017) noted that an important advantage of the DEA-tolerance approach is its reliable identification of the most stable of the best and worst performers. The eco-efficiency assessment of the best- and worst-case scenarios provides a highly conservative estimate of these scores for each WWTP.

5. Conclusions

The assessment of the eco-efficiency of WWTPs is an effective management tool for improving their sustainability. However, it is a challenging task as it requires a holistic approach that integrates several performance indicators into a single index. From a methodological point of view, previous studies have demonstrated that the data envelopment technique exhibits several positive features with which the eco-efficiency of productive units can be evaluated. Nevertheless, traditional data envelopment analysis models do not account for data uncertainties, which is important because eco-efficiency scores are highly sensitive to data errors.

To overcome this limitation, this study is the first to evaluate the eco-efficiency of a sample of WWTPs while simultaneously considering uncertainty in data and integrating greenhouse gas emissions as an undesirable output. The data envelopment analysis-tolerance model was applied for this evaluation. This enabled the computation of the eco-efficiency of each facility for 729 scenarios, and the best and worst cases were identified. The WWTPs were also benchmarked based on their eco-efficiency scores for the scenarios considered.

The primary observations of our study can be summarized as follows: Firstly, indirect greenhouse gas emissions exhibit the lowest tolerance value or the lowest uncertainty in data. This reveals the importance that WWTP managers accord to energy issues. Secondly, based on the average eco-efficiency scores, there is a high scope for improvement in the performances of the WWTPs, from both economic and environmental perspectives. Thirdly, for most of the WWTPs evaluated, the scores computed for the best- and worst-case scenarios change significantly. This highlights the importance of taking uncertainty into account for performance assessments.

From a policy perspective, this study demonstrates the importance of integrating data uncertainty in eco-efficiency assessments. This is further relevant for regions or countries where performance assessment is used to set (waste) water tariffs. Omitting uncertainty data is likely to result in biased conclusions because the ranking of eco-efficient WWTPs changed notably for the scenarios evaluated when this was included. The proposed methodological approach provides a robust and reliable framework for supporting decision-making aimed at improving the sustainability of WWTPs.

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