Eco-efficiency evaluation in wastewater treatment plants considering greenhouse gas emissions through the Data Envelopment Analysis-tolerance model

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ABSTRACT

The eco-efficiency evaluation in wastewater treatment plants (WWTP) is used to know and improve the environmental and economic efficiency of these processes, systems, products and services. The eco-efficiency evaluations in WWTP contemplate: the inputs to be minimized, the desirable results to be maximized and the undesired results to be minimized. Data envelopment analysis (DEA) is a widely used method to evaluate the eco-efficiency of WWTPs, integrating several approaches in a single index, traditional DEA models do not take into account the uncertainty in the data. This study evaluates the eco-efficiency of a sample of Catalan WWTPs, considering the uncertainty of the data (DEA tolerance model), and it is for the first time that together with CO_2, other greenhouse gas (GHG) such as CH_4 and N_2O are they considered as part of the process outputs. GHG emissions were quantified using methods reported in the literature. 729 eco-efficiency scores were estimated for each WWTP instead of a single score like conventional DEA models, analyzing optimistic and pessimistic scenarios. The WWTPs were classified according to the estimated eco-efficiency scores, accounting for the uncertainty in each of the scenarios, and demonstrating the changes in the performance of the WWTPs in the different scenarios. Only two WWTPs were eco-efficient in all the scenarios evaluated. This approach provides essential information to improve efficiency and innovation in the wastewater sector.

Keywords: Uncertainty, Environmental performance, Emission estimation, Process outputs, N_2O emission, CH_4 emission

1. Introduction

The concept of eco-efficiency dates back to the 1970s as the concept of "environmental efficiency" (Huppes and Ishikawa 2007). The term eco-efficiency was introduced in the late 1980s and appeared in the academic literature for the first time in 1989 (Georgopoulou et al. 2014). It was defined as the relationship between the amount of environmental impact and the added value (Gómez et al. 2018; Schaltegger and Sturm 1989). Others define eco-efficiency as a key element to promote fundamental changes in the way societies produce and consume resources and, therefore, to measure progress in green growth (Huppes and Ishikawa 2007). Eco-efficiency plays an important role in expressing how efficient economic activity is concerning to the goods and services of nature. The concept of eco-efficiency has been adopted to use and demonstrate as a practical tool, to improve both the economic and environmental benefits of an activity or sector (Huppes and Ishikawa 2007). Eco-efficiency differs from sustainability in that eco-efficiency does not measure social aspects. The World Business Council for Sustainable Development (WBCSD) defines eco-efficiency as the relationship between the value of the product or service and the environmental influence (GDRC 2019).

In recent years, eco-efficiency assessment has become popular as a management system, which attempts to balance and evaluate environmental and economic performance in different sectors (GDRC 2019; Gómez et al. 2018), such as the industry sector of the water and sanitation (Caiado et al. 2017; Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016). A wastewater treatment plant (WWTP) is a facility that uses a combination of several processes to treat domestic and industrial wastewater, and remove pollutants (Gémar et al. 2018; Gómez et al. 2018; Hreiz et al. 2015). Wastewater treatment plants are a productive unit that uses resources (energy and materials) to eliminate pollutants contained in wastewater, and discharge the raw or partially treated effluent to the environment (Gómez et al. 2018; Ren and Liang 2017). It is essential to quantify the eco-efficiency of WWTPs to improve performance, reduce operating costs, determine operating success, identify and track trends, prioritize actions and identify areas for improvement (Gémar et al. 2018; Molinos-Senante, On Sala-Garrido, et al. 2016). The evaluation of co-efficiency is a useful tool to improve the sustainability of WWTPs. However, it is a complex task that requires the integration of various performance indicators in a single index (Gómez et al. 2018).

A Life-Cycle Assessment (LCA) is a robust method used to quantify the global environmental impact of a product or service (based on a functional unit), it can include social variables in its evaluation through the Social-LCA, and economic aspects through Life Cycle Costing (LCC) (García Besné et al. 2018). The Data Envelopment Analysis (DEA) is a method that has been used to evaluate the eco-efficiency of WWTPs, it provides a synthetic performance index that integrates multiple inputs and outputs (economic and environmental) (Cooper et al. 2007; Gémar et al. 2018), and furthermore, it allows integrating environmental impacts in the eco-efficiency evaluation as undesired results (Gómez et al. 2018). There are non-radial DEA models, such as the Weighted Russell Directional Distance Model (WRDDM). This model differs from radial DEA models in that it allows obtaining an eco-efficiency index for each component involved in the analysis (inputs and outputs, both desirable and undesirable), in addition to generating a global efficiency index over time, taking into account the changes in the performance of WWTPs in an interporal setting (Gémar et al. 2018).

The work carried out previously focused on seeking the control and design of wastewater treatment processes, in which the main problems that affect eco-efficiency are discussed and identified (Hreiz et al. 2015; Lorenzo-Toja et al. 2015), data tolerances are taken into account and obtained improvements in the economic and environmental performance of treatment plants (Gémar et al. 2018; Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016; Molinos-Senante, On Sala-Garrido, et al. 2016). These investigations determine the sustainability of the different treatment processes (Ren and Liang 2017), in addition, they classify the WWTP through scores, considering the costs, elimination of pollutants and the CO_2 emissions produced by the use of energy in each facility (Gémar et al. 2018; Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016). An eco-efficiency evaluation in WWTP must include GHG emissions as outputs of the process, not only the emission of CO_2 from electricity consumption, but also the emissions of CH_4 and N_2O generated during and after treatment, in this way, the eco-efficiency scores of the WWTPs would consider the inputs and outputs of the process, and their classification would be according to their performance and environmental impact.

Other authors have used eco-efficiency analysis to know the changes and impacts in different sectors, unrelated to wastewater treatment (Beltrán-Esteve et al. 2017; García Besné et al. 2018; Georgopoulou et al. 2014; Martzopoulou and Komninos 2019; Yang et al. 2018; Zha et al. 2020).

Eco-efficiency evaluations of WWTP are made up of three basic components: 1) desired results that should be maximized (pollutant removal efficiency), 2) inputs that should be minimized (economic costs), 3) undesirable results that should be minimized (environmental impacts). This DEA approach allows integrating the three dimensions of eco-efficiency (service value, resource consumption and environmental impacts) (Cooper et al. 2007; Gémar et al. 2018; Gómez et al. 2018). By linking environmental and economic performance, eco-efficiency is primarily in a management concept. The implementation of eco-efficiency measures provides entities with a greater understanding of their activities and impacts, since eco-efficiency requires the development of organizational, financial and environmental profiles. Besides, companies or entities that use eco-efficiency principles are more profitable and competitive, because they use fewer virgin resources, water and energy, generate less waste and pollution, improve production methods, develop new products or services, and use or recycle existing materials (GDRC 2019).

This study applies a DEA tolerance model to perform an eco-efficiency analysis of a WWTP sample, taking into account the uncertainty of the data. Unlike previous studies, we included CH_4 and N_2O emissions produced by selected WWTPs. The objective of this article is to calculate eco-efficiency scores, applying for the first time a DEA tolerance model in WWTPs that integrates GHG emissions as desired outputs (value of services provided) and unwanted outputs (effects of the operation of the WWTP on climate change) of the WWTP located in the MAB (Metropolitan Area of Barcelona). GHG emissions are considered as a desired output only when they are used for the production of electricity or as fuels, but not from burning (CH_4) or leakage. 729 scenarios are considered; the best and worst scenarios for each facility are identified and evaluated, in order to show a comparative evaluation of the performance of the WWTPs and promote the sustainable treatment of wastewater. GHG emissions were estimated from quantification methods proposed in the literature. The integration of GHG emissions in the eco-efficiency evaluation gives added value to the scores obtained by each WWTP, allowing us to know the generation of waste and pollution of each one of them.

2. Materials and Methods

2.1 Eco-efficiency evaluation using DEA

To evaluate the eco-efficiency of the WWTPs, we apply the DEA method. DEA is a non-parametric method that allows the construction of efficient production limits, applying linear programming to the inputs and outputs of evaluated units (WWTP for this case) (Cooper et al. 2007; Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016). DEA compares the relationship between inputs and outputs of each plant concerning the other plants (Molinos-Senante, Donoso, et al. 2016). The last result will be an eco-efficiency index that represents how close you are to the production possibilities frontier. Traditionally, DEA methodology uses as performance indicators the inputs and desired outputs (Charnes et al. 1978), however, it is known that in most processes unwanted outputs are also generated, such as, garbage or contaminants (Koopmans 1951). Thus, the DEA method will have performance indicators for inputs and desired and unwanted outputs, as has been previously done in the literature (Fujii et al. 2014; Gémar et al. 2018; Gómez et al. 2018; Monastyrenko 2017).

Given N WWTPs, where each of them $\left(WWTP_j,\ 1 \le j \le N\right)$ has vectors of $x_{mj} = \left(x_{1j}, x_{2j}, \dots, x_{Mj}\right)$ of M inputs, $y_{sj} = \left(y_{1j}, y_{2j}, \dots, y_{Sj}\right)$ of S desirable outputs and L unwanted outputs $b_{lj} = \left(b_{1j}, b_{2j}, \dots, b_{Lj}\right)$. According to the DEA model, the eco-efficiency θ is obtained by solving the following linear programming model for each WWTP (j$_0$):

$$\begin{aligned}
&Min\ \theta \\
&st. \\
&\sum_{j=1}^{N} \lambda_j x_{mj} \le \theta x_{mj_0}\ , \quad 1 \le m \le M \\
&\sum_{j=1}^{N} \lambda_j y_{sj} \ge y_{sj_0}\ , \quad 1 \le s \le S \\
&\sum_{j=1}^{N} \lambda_j b_{lj} = b_{lj_0}\ , \quad 1 \le l \le L \\
&\sum_{j=1}^{N} \lambda_j = 1\ , \\
&\lambda_j \ge 0, \qquad 1 \le j \le N
\end{aligned} \qquad (1)$$

Where λ_j is an intensity vector that fits when solving the model. The eco-efficiency θ, is bounded between 0 and 1, where the maximum value $(\theta = 1)$ implies that said plant is on the frontier of efficiency, the lower values tell us that said plant has improvement possibilities and the minimum value represents that it is completely inefficient$(\theta = 0)$.

2.2 DEA with tolerance model

The main criticism when using DEA models is that it deterministically solves a mathematical model as in Eq. 1, so it does not take into account any type of error or uncertainty in the data provided (Tsolas 2010). To overcome this limitation, we use the DEA model with tolerances, which captures the uncertainty when constructing intervals for the data (Dyson and Shale 2010). Thus, we will able to evaluate how sensitive the eco-efficiency is for each plant, by varying each of its inputs and outputs with a certain tolerance independently. Tolerances are constant, symmetric, positive scalar values; defined from how the inputs and outputs (desired and unwanted) change with respect to the annual average of each of the plants, as represented in the following equation (Eq. 2) for inputs, desired outputs and unwanted outputs:

$$\alpha_{mj} = \left|\bar{x}_{mj} - x_{mj}\right|$$
$$\beta_{sj} = \left|\bar{y}_{sj} - y_{sj}\right|$$
$$\gamma_{lj} = \left|\bar{b}_{lj} - b_{lj}\right| \tag{2}$$

From Eq. 2, we can see that there are an infinity of accessible points to evaluate the model, so we will work with extreme and normal cases, that is, where the tolerances are positive/negative or zero respectively. Thus, the values that our data can take will be (Eq. 3):

Inputs for the WWTP being compared:

$$x_{mj_0}\left(1 - \alpha_{mj_0}\right),\ x_{mj_0}\ ,x_{mj_0}\left(1 + \alpha_{mj_0}\right)$$

Desired outputs for the WWTP being compared:

$$y_{sj_0}\left(1 - \beta_{sj_0}\right),\ y_{sj_0}\ ,y_{sj_0}\left(1 + \beta_{sj_0}\right)$$

Unwanted outputs for the WWTP being compared:

$$b_{lj_0}\left(1 - \gamma_{lj_0}\right),\ b_{lj_0}\ ,b_{lj_0}\left(1 + \gamma_{lj_0}\right)$$

WWTP inputs:

$$x_{mj}\left(1 - \alpha_{mj}\right),\ x_{mj}\ ,x_{mj}\left(1 + \alpha_{mj}\right)$$

Desired outputs from the WWTP:

$$y_{sj}\left(1 - \beta_{sj}\right),\ y_{sj}\ ,y_{sj}\left(1 + \beta_{sj_0}\right)$$

Unwanted outputs from the WWTP:

$$b_{lj}\left(1 - \gamma_{lj}\right),\ b_{lj}\ ,b_{lj}\left(1 + \gamma_{lj}\right) \tag{3}$$

Evaluating these combinations represents solving 3^6 times the Eq. 1 for each plant (j_0). We have three situations: a) favorable, positive tolerance, b) unfavorable, negative tolerance and c) original, zero tolerance; with six possible inputs and outputs (desired and unwanted): i) inputs from the analyzed WWTP, ii) desired output from the analyzed WWTP, iii) unwanted output from the analyzed WWTP, iv) inputs from the rest of the WWTPs, v) desirable outputs from the rest of the WWTPs, and vi) unwanted outputs from the rest of the WWTPs. These combinations ensure that we study the best and worst possible scenario for each of the plants.

The best scenario for a WWTP (j_0) occurs when there is a minimum at the input, the desired output is maximum and the unwanted output is minimum; and the opposite for the rest of the plants. Thus, the worst scenario would imply the opposite, that is, a reversal of the signs. Mathematically it is expressed (Eq. 4):

$$x_{mj} \begin{cases} x_{mj_0}\left(1 \mp \alpha_{mj_0}\right) \\ x_{mj}\left(1 \pm \alpha_{mj}\right) \end{cases}$$

$$y_{sj} \begin{cases} y_{sj_0}\left(1 \mp \beta_{sj_0}\right) \\ y_{sj}\left(1 \mp \beta_{sj}\right) \end{cases}$$

$$b_{lj} \begin{cases} b_{lj_0}\left(1 \mp \gamma_{lj_0}\right) \\ b_{lj}\left(1 \pm \gamma_{lj}\right) \end{cases} \tag{4}$$

In the best and worst scenarios, the maximum and minimum eco-efficiency indices are obtained respectively, for each WWTP evaluated, which allows reducing the uncertainty of the eco-efficiency evaluation.

2.3 Ranking of treatment plants

One of the objectives of the eco-efficiency evaluation is to compare the evaluated WWTPs, classifying the WWTPs according to their eco-efficiency scores obtained from the DEA model with tolerances. Since several WWTPs can be identified as eco-efficiency (score equal to 1), they cannot be classified directly (Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016). Using the values obtained from linear programming (optimization), plants can be ranked (or classified) from the efficiency indices obtained from the DEA estimation model with tolerances (Boscá et al. 2011). This model proposes two indicators for ranking the treatment plants based on the number of times they are called efficient within the different scenarios previously calculated (Boscá et al. 2011).

The two indicators are the following:

$$R_{k0}^{1} = \frac{e_{k0}}{T_{k0}} \tag{5}$$

$$R_{k0}^{2} = \begin{cases} \frac{S_{k0} - e_{k0}}{\tau_{k0} - e_{k0}} & if\ \tau_{k0} \neq e_{k0} \\ & 0\ if\ R_{k0}^{1} = 1 \end{cases} \tag{6}$$

Where e_{k0} is the times that the eco-efficiency index of the WWTP k_0 is equal to one; τ_{k0} is equal to the number of scenarios analyzed per plant and S_{k0} is the sum of the eco-efficiency indices of plant k_0.

R^1_{k0} is between zero and one and denotes the proportion of time that plant k_0 is eco-efficient. A value of one means that the evaluated plant was eco-efficient in all the simulated scenarios, so a plant with a higher value of R^1_{k0} is more likely to be eco-efficient (Sala-Garrido et al. 2012). A value of zero means that the k_0 plant was eco-inefficient in all the evaluated scenarios. The R^2_{k0} indicator is also between zero and one and is used to rank two plants with identical R^1_{k0} values.

2.4 CH_4 emission estimate

Eq. 7 was used to estimate the CH_4 emission from the treatment plants. This is a simplified equation of the IPCC (2006) methodology, used by Paredes et al. (2019). Additionally, the correction factors (MCF) proposed by Noyola et al. (2018) were considered. Eq. 7 estimates the emission of CH_4 in this study. This simplified version does not consider the R term (amount of methane recovered per wastewater treatment inventory year) for its application in individual facilities, it compares the total CH_4 production of the facilities regardless of the biogas management in each one (captured in filters extracted from anaerobic treatment ponds and/or recovered from anaerobic sludge digestion), which can be used for burning and power generation (IPCC 2019; Paredes et al. 2019). La energy co-generated by the MAB WWTPs was 40,605 MWh in 2015 and 41,821 MWH in 2016, used for own consumption in the generation of thermal and electrical energy (AMB 2016). The refinement of the IPCC Guidelines provides the default value for CH_4 recovery equal to zero (IPCC 2019). It was decided to use the MCF modification proposed by Noyola et al. (2018), since the IPCC MCFs overestimate the emission of CH_4 according to the literature found (Delre et al. 2017; Paredes et al. 2015, 2019).

$$CH_{4\ \mathrm{Emissions}} = B_o \bullet MCF\ (TOW - S) \qquad (7)$$

Where B_o is the maximum CH_4 production capacity per BOD removed (kg CH_4/kg BOD_{rem}) from the wastewater or sludge; MCF is the correction factor for CH_4; TOW is the total organic matter in the wastewater entering the treatment facility per year (kg BOD/year) and S is the organic component (sludge) removed from the facility per year (kg BOD/year, the value obtained of Metcalf & Eddy et al. (2014)).

The MCFs used in this study, by type of treatment are: 0.06 for a centralized aerobic treatment plant; 0.32 for a centralized aerobic treatment plant with anaerobic sludge digesters; 0.08 for centralized anaerobic (or anoxic) aerobic treatment plant; 0.34 for a centralized, anaerobic (or anoxic) aerobic treatment plant with anaerobic sludge digesters (Noyola et al. 2018).

The TOW value was obtained with the operational data of each analyzed plant. For practical purposes, the value of S was obtained from the values proposed by Metcalf & Eddy et al. (2014), which resulted in 45% TOW, which is removed from volatile solids as the sludge is digested anaerobically.

2.5 N_2O emission estimate

The N_2O plant emission of the advanced WWTPs analyzed in this study was estimated using the methodology proposed by Snip (2010) and the modification in the Emission Factor (EF) proposed by Ramírez-Melgarejo et al. (2020) (Eq. 8). This methodology considers as the value of Total

Nitrogen (TN) entering the plant as the main parameter to determine the content of N in the wastewater. Effluent emission from advanced WWTPs is estimated using the IPCC (2019) methodology and the modification in the range of the EF of Ramírez-Melgarejo et al. (2020) (Eq. 9).

$$N_2O_{emission} = Q \bullet N_{total} \bullet EF \qquad (8)$$

$$N_2O_{EFFLUENT,DOM} = N_{EFFLUENT,DOM} \bullet EF_{EFFLUENT} \bullet 44/28 \qquad (9)$$

Where $N_2O_{emission}$ is the emission of N_2O in the inventory year (kg N_2O/year); Q is the inflow to each treatment plant (m^3/day); N_{total} is the amount of nitrogen entering the plant per day (kg N/day); EF is the emission factor for N_2O emissions from discharged wastewater (0.03 kg N_2O-N/kg N); $N_{Effluent,\ dom}$ is the amount of nitrogen in the effluents discharged to the aquatic environment (kg N/day); 44/48 molecular weight conversion (g N_2O per g N emitted as N_2O).

The plant emission of the traditional WWTP analyzed in this study was estimated using the methodology proposed by the IPCC (2019), it also considers TN as the determining parameter to know the N content in wastewater (Eq. 10). The effluent emission from the analyzed WWTPs is estimated using the IPCC (2019) methodology (Eq. 9 and Eq. 11), incorporating a modification proposed by Ramírez-Melgarejo et al. (2020) in the EF. Due to the lack of information that exists on the behavior of N_2O in the aquatic environment, indirect emissions continue to be estimated using the IPCC methodology, which is based on the parameter of per capita protein consumption, the population served and default values (IPCC 2006, 2019).

$$N_2O\ Plants_{DOM} = [\Sigma(U_i \bullet T_{ij} \bullet EF_j)] \bullet TN_{DOM} \bullet 44/28 \qquad (10)$$

$$N_{EFFLUENT,DOM} = \Sigma[(TN_{DOM} \bullet T_j) \bullet (1 - N_{REM,j})] \qquad (11)$$

Where $N_2O\ Plants_{DOM}$ are the N_2O emissions from domestic wastewater treatment plants in inventory, kg N_2O/year; U_i is the fraction of population of income group *i* in inventory year; T_{ij} is the degree of utilization of the treatment/discharge pathway or system j, for each fraction income group *i* in inventory year; *i* is the income group: rural, urban high income and urban low income; J is each treatment/discharge pathway or system; EF_j is the emission factor for the treatment/discharge pathway or system j, kg N_2O-N/kg N; TN_{DOM} is the total nitrogen in domestic wastewater in inventory year, kg N/year ($TN_{DOM\_j} = (P_{treatment\_j} \times Protein \times F_{NPR} \times N_{HH} \times F_{NON\text{-}CON} \times F_{IND\text{-}COM})$); $P_{treatment}$ is the population served, inhabitants; Protein is the annual protein consumption per capita, kg/person/year (Available at FAO (2019), Food and Agriculture Organization: Spain= 38.32 kg/inhabitant/2015 and 39.42 kg/inhabitant/2016); F_{NPR} is the fraction of nitrogen in the protein (0.16 kg N/kg protein); $F_{NON\text{-}CON}$ is the factor for unconsumed protein added to wastewater (1.1 for countries without garbage disposal and 1.4 for countries with garbage disposal); $F_{IND\text{-}COM}$ is the co-discharged industrial and commercial protein fraction (1.25); N_{HH} is the additional nitrogen from household products added to wastewater, default= 1.1; $EF_{EFFLUENT}$ is the emission factor for N_2O emission from discharged wastewater (0.03 kg N_2O-N/kg N); 44/28 conversion from kg N_2O-N to kg N_2O.; $N_{EFFLUENT}$ is the nitrogen in the effluent discharged to the aquatic environment (kg N/year); $N_{REM,j}$ is the fraction of total nitrogen from wastewater removed during wastewater treatment by treatment type (IPCC 2019).

The estimates of plant emissions are considered as avoided emissions (desired outputs), when applying treatment to wastewater, the pollutants present reduce their concentration percentages (according to the type of treatment used by the plant), avoiding an impact greater in the aquatic environment where the effluent is discharged (crude or partially treated) (IPCC 2019). Effluent emissions are considered unwanted emissions, which are generated by the discharge of the effluent into the natural environment, due to the remaining nitrogen content in the wastewater and the oxygenation level of the aquatic environment. The emission in the natural environment is the emission that wants to be avoided, to generate less waste and less pollution to the environment (IPCC 2019).

2.6 Sample description

The wastewater treatment plants of the MAB are analyzed in 2015 and 2016. The operating data were provided by the Technical Area of Sanitation and Inspection of the MAB. The MAB in Spain has seven treatment plants, five of an advanced type (with nutrient removal) and two of a traditional type. These WWTPs present a secondary biological treatment technology. WWTPs 1, 2, 4, 6 and 7 are biological treatment plants with nutrient removal/reduction, and WWTPs 3 and 5 are traditional biological treatment plants. The sample WWTPs have an installed treatment capacity of 13,370 l/s, ranging from 8 l/s to approximately 3,870 l/s. The advanced type WWTPs apply anaerobic digestion treatment for energy cogeneration, as well as mechanical dehydration and thermal drying of the sludge produced; unlike the traditional type WWTPs that only dehydrate their generated sludge. The MAB has 100% sewerage coverage and treats 100% of the wastewater of a total of 3,214,211 inhabitants (AMB 2016).

WWTP eco-efficiency studies are based on the selection of inputs, desired outputs and unwanted outputs (Table 1). Table 1 contains the variables used in this study. This table contains the costs, operating data and direct and indirect emissions of CH_4 and N_2O from the WWTPs analyzed in 2015 and 2016. The inputs are the resources consumed by each plant, the operating and maintenance costs, expressed in €/year. For this study, only the total cost of the m^3 of treated water per year was obtained, so we do not have the separation of operating costs and maintenance costs (Agència Catalana de l`Aigua 2020). From the operational characteristics of the WWTP analyzed in this study, three desired outputs were taken into account: the organic matter removed (expressed in Biochemical Oxygen Demand, BOD_5), the emission of N_2O avoided with the wastewater treatment and the CH_4 emission avoided with wastewater treatment (direct emissions). These variables are expressed in tCO_2e/year and consider the characteristics of the inlet and outlet flow of each plant.

Table 1. Sample description

	Inputs	Desirable Outputs			Undesirable Outputs
	Total operating costs (€/year)	Organic matter removed (tBOD/year)	N_2O emission avoided by water treatment (tCO_2e/year)	CH_4 emission avoided by water treatment (tCO_2e/year)	Indirect GHG emissions (tCO_2e/year)
Average	89,816,485	17,917	35,852	82,227	25,894
SD	111,330,133	25,098	44,340	115,015	37,486
Minimum	632,936	59	201	270	73
Maximum	301,775,325	70,763	114,975	324,038	108,018

This study is a pioneer in integrating GHG emissions as desired outputs and unwanted outputs in the eco-efficiency evaluations of WWTP. It not only considers electricity consumption as an emission produced by water treatment, but also includes the emission of CH_4 and N_2O. This study seeks to show how the good or poor functioning of a WWTP affects climate change. Depending on the type of treatment, GHGs (CO_2, CH_4 and N_2O) will be produced, either directly or indirectly (Jungdorf et al. 2017). For this, direct emissions are considered desired outputs (plant emission), since they are emissions from sources that are owned and controlled by each WWTP, thus avoiding their occurrence in the aquatic environment where the effluent is discharged. Indirect GHG emissions are considered an unwanted output (tCO_2e) produced by the WWTPs (emission in the natural environment where the effluent is discharged), they are the emissions as a consequence of the activity of the WWTP that are produced in external sources, and that includes the emissions of the energy consumed by treatment plants (GHG Protocol 2014).

The 7 WWTPs of the MAB reduce nitrogen and control its concentration in the effluent, so that from the numerical methods proposed in the literature it was possible to estimate the direct and indirect emission of N_2O produced in each of the WWTPs. N_2O is a GHG that is emitted during wastewater treatment. N_2O is formed from material contained in wastewater in the form of urea, ammonia and food proteins (Farrell et al. 2005; Gupta and Singh 2012; Kampschreur et al. 2009; Thomsen and Lyck 2005). N_2O has a Global Warming Potential (GWP) of 298 times that of CO_2 with a 100-year projection (Myhre et al. 2013). The main factor in determining the potential to generate N_2O in wastewater is its nitrogen content (CH2M HILL 2007). N_2O in an advanced WWTP is generated as a by-product during the nitrification/denitrification process (nutrient removal) (CH2M HILL 2007; Hwang et al. 2016; Kampschreur et al. 2009; Scheehle and Doorn 2004; Thomsen and Lyck 2005), where it is transformed and emitted as nitrogen gas (N_2) (direct emission) or in the natural environment where the effluent is discharged (indirect emission), either raw or partially treated, due to the remaining nitrogen content in water (CH2M HILL 2007; Farrell et al. 2005). Due to the complexity involved in measuring N_2O emissions in WWTPs and the lack of standardized measurement methods, N_2O measurements for the wastewater sector have been estimated from numerical methods, without the contribution of measured data (Law et al. 2012).

CH_4 emission was also estimated from a quantification method proposed in the literature, since these evaluated plants treat their sludge anaerobically. CH_4 is produced from the biological degradation of organic matter in anaerobic conditions of water or sewage sludge, it is a flammable gas that can be captured and used to generate electricity or heat (IPCC 2015; Lara and Préndez 2003). The GWP of CH_4 is equivalent to 34 tCO_2e over a 100-year period (Myhre et al. 2013). The CH_4 emission is considered a desirable output, as it is a direct emission from the WWTP, and therefore an emission avoided with wastewater treatment.

The IPCC Guidelines do not consider the CO_2 emission from a WWTP as an anthropogenic emission since it returns to the atmosphere naturally in equilibrium with its atmospheric concentration (IPCC 2006, 2019), a consideration that may differ since wastewater contains detergents, oils and fats of synthetic origin (Lara and Préndez 2003; Nolasco 2010). In this study, the electrical energy consumed by the facilities was considered as an unwanted output, as part of the eco-efficiency evaluation of a WWTP. The emission was estimated based on the reports of the electrical energy consumed per year by the facilities (kWh/year) (AMB 2016), and the electricity mix of the marketers in Spain in 2015 and 2016 (kg CO_2e/kW) (Ministerio para la Transición Ecológica y el Reto Demográfico 2018).

3. Results and discussion

3.1 Estimation of tolerance for inputs and outputs

The first step to obtain the eco-efficiency scores of the WWTP evaluated in this study was to estimate the tolerance values (series of historical observations of each variable) using data from two years (2015 and 2016), for each of the variables considered (total operating costs, organic matter removed, N_2O emission avoided with wastewater treatment, CH_4 emission avoided with treatment and indirect GHG emissions) in the DEA tolerance model. The tolerance values (Table 2) reflect the potential uncertainty of the data for each variable (annual averages of the inputs and outputs of each of the WWTPs). Table 2 contains the values of the estimated tolerances for the inputs, desired outputs and unwanted outputs considered in this study. It should be remembered that the unwanted outputs (indirect GHG emissions) consider the electricity consumption per year of each WWTP and the indirect emission of N_2O.

Table 2. Tolerances for input, desirable outputs and unwanted outputs, %

Total operating costs	**Organic matter removed**	**N_2O emission avoided by treatment**	**CH_4 emission avoided by treatment**	**Indirect GHG emissions**
1.12	11.28	7.59	11.11	3.29

The reduction of pollutants (desired outputs) has the highest tolerance values (similar tolerance values), being the removal of organic matter (BOD_5) and the emission of CH_4 that is avoided with the treatment, who present a greater variability (uncertainty). This shows the technical and operational efforts made in the WWTPs over time, according to the needs of each facility and in benefit of the reduction of pollutants and CH_4 emissions (variables directly managed by each WWTP). The desired output of the N_2O emission that is avoided with the treatment also has a high tolerance value (variables managed by each WWTP). N_2O has a global warming power of 298 tCO_2e, which implies a significant impact on the environment and ecosystems, hence the importance of reducing and avoiding the emission of this GHG with the treatment of wastewater. All this based on the correct application of environmental regulations at the European Union level, in compliance with the concentration of pollutants in the effluent (Directive 91/271/ECC: Treatment of urban wastewater). The GHG emission (unwanted output) has a low tolerance value, this highlights the importance and commitment of the MAB to minimize indirect emissions caused by wastewater treatment. The operating costs (the input) present the lowest tolerance value, which implies that this variable exhibits the lowest uncertainty in the eco-efficiency evaluations of the WWTPs. The data limitation at the time of this study must be taken into account, only the total cost of treatment was obtained, without division of staff, operation and maintenance expenses.

3.2 Eco-efficiency scores of the WWTPs analyzed

Once the tolerances for inputs and outputs of the 7 WWTPs were obtained, the eco-efficiency scores were estimated. 729 eco-efficiency scores were generated with an equal number of probable scenarios, the result of the implementation of the DEA tolerance model and the inclusion of undesired results. These values produced a range of variation within the eco-efficiency scores, thus reducing the uncertainty in the eco-efficiency of each WWTP. Eco-efficiency scores were selected in four specific groups (Table 3): the original (score obtained from the original data), the mean (average eco-efficiency score of the evaluated scenarios), the maximum (score of eco-efficiency obtained and represents the best scenario of the evaluated WWTPs) and the minimum (lowest score obtained and represents the worst scenario of the evaluated WWTPs) (Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016).

The results obtained from the original data of each WWTP show that the average eco-efficiency of the 7 evaluated WWTPs of the MAB was 0.929, with a potential improvement of 7.1% in terms of cost, the reduction of GHG emissions and improvement in pollutant removal efficiency. This result shows the economic and environmental interest and commitment of this study area, by applying treatment to 100% of its wastewater generated by its population and reducing the pollutants present. In the best-case scenario, the maximum average eco-efficiency score of the treatment plants could reach 0.967, which would require an improvement of approximately 3.3%. In the worst-case scenario, the average minimum eco-efficiency score was 0.786, with a potential improvement of 21.4%. The average eco-efficiency score of the evaluated scenarios was 0.876, with a difference of 12% with respect to the average score using the original data. Table 3 shows the eco-efficiency scores of the 7 evaluated WWTPs of the MAB, and the standard deviations obtained from the evaluated scenarios. The minimum eco-efficiency score with the original data was 0.650, this could be considered a low eco-efficiency value, since it indicates that this plant could improve its eco-efficient potential by 35% compared to the most eco-efficient. These eco-efficiency scores of the 7 AMB WWTPs can be considered acceptable-good, since they are above half the whole number, achieving good performance in the operation and management of each plant.

Table 3. Eco-efficiency scores of the WWTP in the evaluated scenarios

WWTP	**Original**	**Mean**	**Maximum**	**Minimum**	**Amplitude (max - min) (%)**
1	1.000	1.000	1.000	1.000	0.00
2	0.850	0.863	1.000	0.720	28.00
3	1.000	0.979	1.000	0.930	7.00
4	1.000	0.940	1.000	0.840	16.00
5	0.650	0.642	0.770	0.520	25.00
6	1.000	0.710	1.000	0.490	51.00
7	1.000	1.000	1.000	1.000	0.00
Mean	0.929	0.876	0.967	0.786	18.14
SD	0.135	0.135	0.080	0.199	16.95

In Table 3 it can be seen that five of the seven WWTP (71%) were eco-efficient based on their original data, which indicates that they were at the efficient frontier and are the WWTP with the best yields. These five WWTPs constitute the benchmark for best practices. The two eco-inefficient WWTPs had low nitrogen reduction (pollutant reduction) percentages (approx. 20-30%) in 2015. One of the two eco-inefficient WWTP could become eco-efficient in the best of the scenarios, since it increased its percentage of reduction of nitrogen content in the wastewater that is treated in 2016, in this way, this reduction of pollutants also it is reflected in the GHG emissions that were produced and are within defined tolerance values. This shows that in the most favorable scenario, six of the seven WWTP (86%) would probably be eco-efficient, but one of the seven would not become eco-efficient even in the best of the scenarios. This eco-inefficient WWTP is a traditional type plant with low pollutant reduction percentages, and therefore, the GHG emissions that are produced are almost entirely unwanted outputs. By reducing only 30% of the pollutants in the wastewater, the GHG emission (N_2O emission) occurs in the natural environment where the effluent, either raw or partially treated, is discharged, increasing the score of the undesirable output of this WWTP.

If we focus on the worst-case scenario, two of the seven WWTP (29%) were identified as eco-efficient, which implies that three facilities that were considered eco-efficient based on their original data are no longer so in the scenario more pessimistic. From a management approach, these WWTP should be attentive to marginal changes in their performance, use of inputs and even quality problems, which could cause them to lose their eco-efficiency status. With these results, the importance of considering uncertainty in eco-efficiency evaluations is appreciated (Gómez et al. 2018). It should be noted that only two WWTP were eco-efficient in the four scenarios evaluated.

As in the worst-case scenario, in the mean scenario, only two of the WWTP were eco-efficient. The average efficiency for the mean scenario is similar to the efficiency scores calculated with the original data from the set of WWTPs in the study area (operation data). These results mean that when the efficiency of the WWTP in this area as a whole is evaluated, the mean value obtained considering the uncertainty is similar to that obtained from the original data. When the evaluation is focused on the level of each WWTP, considering the uncertainty of the data acquires greater relevance, some of the plants present a difference between the results of the original data and the mean of the evaluated scenarios (Molinos-Senante, Donoso, et al. 2016).

Considering GHG emissions (CH_4 and N_2O) as part of the damages avoided (GHG not generated when applying treatment) by treating wastewater gives us a global vision of the importance of treating wastewater and its cost-benefit ratio. Avoiding the negative impact on the bodies of water where the effluent is discharged is the main objective of a WWTP, and when carrying out an eco-efficiency evaluation we verify the correct operation or not of the plant, its points of improvement and the GHG emissions that is avoided when applying the treatment (direct emission). Direct emission is a desired output, it is the emission that is avoided by applying treatment to wastewater. If treatment were not applied, the emission would occur in the natural receiving environment, with 100% unwanted output. It is important to know and consider the GHG emission that is avoided with the treatment, in order to give a level of eco-efficiency to a WWTP. By reducing wastewater pollutants in the plant, it is considered that the indirect emission of N_2O will be of less impact and the eco-efficiency score of the WWTP will be high, based on its percentages of pollutant reduction. There are few studies of the impact and generation that occurs in the natural environment where the discharge is carried out, and the emission factor that the generation produces (conditions and temperature of the environment), therefore the importance of reducing pollutants as part of the treatment (Ramírez-Melgarejo et al. 2020). The key points to improve the eco-efficiency of a WWTP will be: increase its pollutant removal efficiency or reduce its operating and maintenance costs and GHG emissions within the defined tolerance values (Gómez et al. 2018).

Fig. 1 illustrates the ranges of variation (data uncertainty) between the best and worst evaluated scenarios, and the mean values of the eco-efficiency scores of the WWTPs. The different lengths of the bars show the degree to which the uncertainties in the inputs, desirable outputs and undesirable outputs impact the eco-efficiency scores of each plant, indicating the stability of the eco-efficient scores obtained with the analysis. A large width of the bar reveals that there are large differences in the scores between the best and worst-case scenarios, that is, the uncertainty of the data has a great impact on the latter (the WWTP can improve or worsen significantly when changing their inputs and/or outputs). A low amplitude indicates that the eco-efficiency will change minimally regardless of variations in the data.

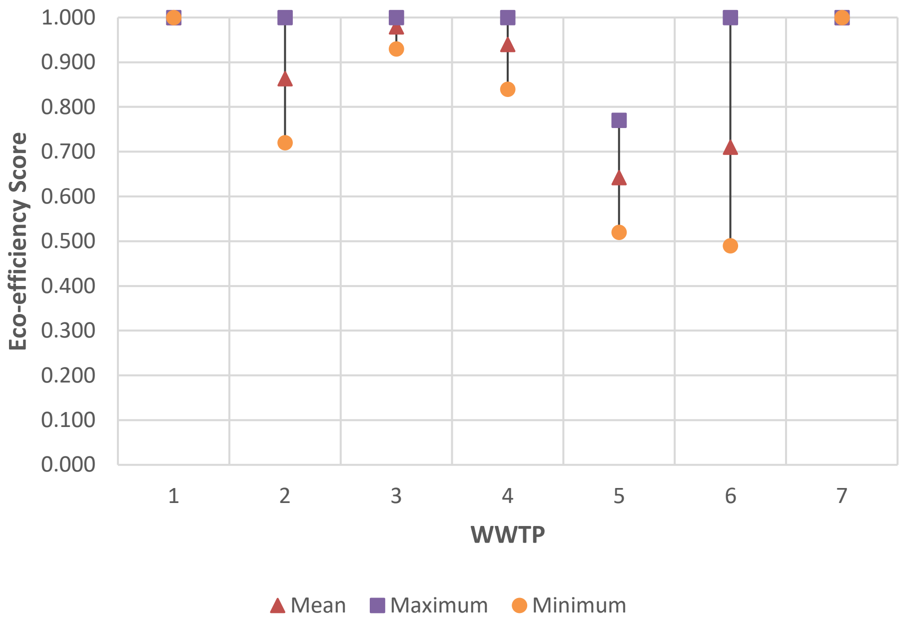

Fig. 1 Eco-efficiency scores of each WWTP for the evaluated scenarios: maximum, average and minimum score

Fig. 1 shows that two of the analyzed WWTPs are eco-efficient in all the evaluated scenarios, the uncertainty of the data does not affect the eco-efficiency of these plants. WWTP 3 and 4 show low variability in their eco-efficiency scores obtained, which indicates that their scores do not differ drastically in either the best or the worst-case scenarios. WWTP 2 does not present low eco-efficiency scores although it does show a variability in its uncertainty, for example, plant 2 obtained eco-efficiency scores of 1 and 0.72 in the best and worst-case scenarios, respectively. WWTP 5 does present a low eco-efficiency score concerning the other WWTPs analyzed, although it is still a plant with an acceptable level of eco-efficiency, with eco-efficiency scores of 0.77 and 0.52 in the best and worst of the stages. Only one of the WWTPs presented a great amplitude between its maximum and minimum eco-efficiency scores, being a plant highly sensitive to the uncertainty intervals in its eco-efficiency scores obtained, having a score that oscillates between a minimum of 0.49 and a maximum of 1 in its worst and best of the evaluated scenarios. For the MAB WWTPs, the mean range between the best and worst-scenarios is 18%. It should be noted that the WWTPs evaluated are not a homogeneous group. The results indicate that 6 of the 7 (86%) WWPT present amplitudes lower than 30%, and that only one WWTP presented a greater amplitude, reaching a maximum value of 51%.

It is very effective to compare the sensitivities of the different treatment facilities to the uncertainty of the data when evaluating the eco-efficiency for a correct management of the WWTP (Gómez et al. 2018), in the sense that its performance may be little or very affected by the tolerance values. It is important to have reliable and truthful information on the performance indicators of the treatment facilities to make and propose improvements, according to the scores obtained in the eco-efficiency evaluation (Gómez et al. 2018).

3.3 Classification of WWTPs based on eco-efficiency scores

Based on the R calculated for each plant (R^1_{k0} and R^2_{k0}), the WWTPs were classified according to their eco-efficiency scores obtained in each of the evaluated scenarios. This type of classification is more robust, as it is based on numerous eco-efficiency estimates rather than a single estimate. Table 4 contains the values of both indicators for each of the WWTP evaluated in this study.

WWTPs 1 and 7 occupy the first position in the classification since they present the best performance in the evaluated scenarios when uncertainty is introduced in the eco-efficiency evaluation. When eco-efficiency was evaluated using the original data (Table 3), these WWTPs had an eco-efficiency score equal to 1, that is, they were identified as eco-efficient. By adding the uncertainty of the data in the assessment, this generated a more precise classification of the WWTPs based on eco-efficiency scores. According to the values of R^1_{k0}, WWTP 4, 3 and 6 occupy the subsequent positions in the classification. These WWTPs were eco-efficient in the original and optimistic scenarios, but in the pessimistic scenario they were eco-inefficient and therefore their value of R^1_{k0} is less than unity. Table 4 shows that the R^1_{k0} for WWTP 4 was 0.311, indicating that in 31.1% of the evaluations (227 scenarios), this facility was eco-efficient. WWTP 5 could never be eco-efficient even in the optimistic scenario, since its value of R^1_{k0} is equal to zero, which indicates that it was identified as eco-inefficient in all the evaluated scenarios. Let us remember that WWTP 5 is a traditional type treatment plant with a low percentage of pollutant reduction, and when compared with the capacity and percentages of pollutant reduction of the other WWTPs in the area, it has a lower eco-efficiency score.

WWTPs 1 and 7 are small treatment plants, with a population of 4,000-6,000 inhabitants served, an installed capacity of 258,000-34,000 m^3/year and with nitrogen reduction percentages of at least 80%, which allows them to have a better control in its operation and daily management, reflected in the returns achieved in each one of the evaluated scenarios. WWTPs 4 and 3 are the largest treatment plants in the study area, they contain 81% of the total population served, and have nitrogen reduction percentages of 43-77%. WWTPs 6 and 2 must be attentive to unforeseen changes in inputs and outputs, they are advanced treatment plants with an installed capacity that ranges between 13-17 million m^3/year of treated wastewater, with nitrogen reduction percentages 23-81%. WWTP 5 is a traditional type treatment plant with low percentages of reduction of pollutants that range between 27% and 32%. It should be noted that the 5 advanced treatment WWTPs (plants 1, 2, 4, 6 and 7) treat their produced sludge to generate electrical and thermal energy for their own consumption (desired CH_4 output), in addition that a percentage of stabilized sludge is used in compost and as alternative fuel. For this reason, the desired outputs of these plants are higher, and it gives them a high eco-efficiency score. WWTPs 3 and 5 by dehydration and thermal drying, use the dry sludge in agriculture and cement (AMB 2016).

The results of the R^2_{k0} indicator facilitate the classification of WWTPs that have the same value as R^1_{k0}. In this study, the R^2_{k0} values helped to classify WWTPs 4, 3 and 6 whose R^1_{k0} values were the same (Table 4). These WWTPs had identical eco-efficiency scores when the original data were used to calculate them, but they performed differently in the pessimistic scenario. The R^2_{k0} indicator made it possible to classify the WWTP with an R^1_{k0} equal to zero, referring to plants that were not identified as eco-efficient even in the optimistic scenario. Table 4 identifies WWTP 2 as eco-efficient in the optimistic scenario and WWTP 5 as the least eco-efficient facility, even in the optimistic scenario.

Table 4. WWTP classification based on eco-efficiency scores for the evaluated scenarios

WWTP	R^1_{k0}	R^2_{k0}
1	1.000	-
7	1.000	-
4	0.311	0.912
3	0.279	0.970
6	0.243	0.616
2	0.095	0.848
5	0.000	0.642

Classifying WWTPs in a hierarchical way allows wastewater regulators to compare the eco-efficiency of WWTPs that apply the same regulatory framework (Gómez et al. 2018; Molinos-Senante, Donoso, et al. 2016). This issue is of great interest to environmental authorities, who ensure compliance with laws related to the environment and sustainability, applied to the correct management of WWTPs. In this way, environmental authorities receive more complete and reliable information (Molinos-Senante, Donoso, et al. 2016), for decision-making when establishing budgets, interventions or improvements to treatment plants. The eco-efficiency evaluation of the optimistic and pessimistic scenarios provides a moderate estimate of these scores for each WWTP (Gómez et al. 2018).

4. Conclusions

In recent years, interest has increased in evaluating the eco-efficiency of WWTPs and thus knowing their effectiveness and sustainability, considering the inputs and outputs of the process. Eco-efficiency evaluations in WWTP consider: inputs to be minimized, desirable results to be maximize and undesired results to be minimize. The DEA method is a widely used method for evaluating the eco-efficiency of WWTPs, applying several approaches in a single index. This type of approach has many positive features but does not take into account uncertainty in the data.

To overcome this limitation, this study evaluates the eco-efficiency of a sample of WWTP, considering the uncertainty of the data and, being the first to integrate GHG emissions as desired and unwanted output. To carry out this evaluation, the DEA tolerance model was used, which introduces statistical tolerances in the data. By applying this approach, 729 eco-efficiency scores were estimated for each WWTP, analyzing optimistic and pessimistic scenarios. Using the estimated eco-efficiency scores, the WWTPs were classified according to their eco-efficiency, accounting for the uncertainty in each of the scenarios considered.

The results of a sample of 7 MAB WWTPs provide the following results: 1) indirect GHG emissions (electricity consumption and N_2O emissions) present a low tolerance value. This reveals the importance that WWTP administrators attach to the indirect emissions produced from wastewater treatment, and the operational efforts made to reduce the pollutants that are discharged into the natural environment and the correct management of electricity consumption. The tolerance values of the outlets show the different efforts made by the WWTPs to improve water services and the impact they generate. 2) Using the original data, 5 plants were identified as eco-efficient, this figure increased to 6 plants in the optimistic scenario and reduced to 2 plants in the pessimistic scenario. 3) According to the WWTP classification, only two eco-efficient plants were identified in all the evaluated scenarios. The scores obtained for each WWTP change significantly between scenarios, highlighting the importance of taking into account uncertainty in performance evaluations.

From a political perspective, this study shows that in order to carry out eco-efficiency evaluations of WWTPs it is important to take into account the uncertainty of the data. If the uncertainty of the data is not taken into account, biased results would be obtained, preventing the identification of WWTPs whose eco-efficiency could vary significantly under small changes in the inputs or outputs. Considering GHG emissions as desired and unwanted outputs allows to have a global perspective of environmental and economic performance, allowing to understand the activities and impacts generated by a treatment plant (resources, waste and pollution). By using the DEA model with statistical tolerances and classifying the WWTPs, it provides the authorities of each region with the necessary information for decision-making in the implementation of productivity improvements, efficiency management, and innovation in the WWTPs and in the establishment of the waste treatment and/or management fee.

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