Environmental Impact Assessment Review 69 (2018) 24–31

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

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

Assessing changes in eco-productivity of wastewater treatment plants: The role of costs, pollutant removal efficiency, and greenhouse gas emissions

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ARTICLE INFO

Keywords:
Wastewater treatment
Eco-productivity
Dynamic eco-efficiency
Undesirable outputs
Data envelopment analysis
Luenberger productivity indicator

ABSTRACT

Improving eco-efficiency of wastewater treatment plants (WWTPs) has been identified as being essential for achieving urban sustainability. Several previous papers have evaluated the eco-efficiency of WWTPs using data envelopment analysis (DEA) models. However, those models provided only a static assessment in that they ignored possible fluctuations over time within each plant. To overcome this temporal limitation, this paper evaluates dynamic eco-efficiency (changes in eco-productivity over time) of WWTPs using the dynamic weighted Russell directional distance model (WRDDM). This approach allows one to obtain an eco-productivity change index for each major component of the WRDDM model (costs, pollutants removal, and greenhouse gas emissions). Our results illustrate that although eco-productivity improved in half of the WWTPs we assessed, there was still potential for improving some eco-efficiency components. Moreover, operational costs and greenhouse gases emissions were the main drivers reducing eco-productivity. This paper demonstrates the importance of evaluating change in eco-productivity over time and in identifying the drivers associated with those changes, both of which can be used to support decision-making focused on the sustainability of WWTPs.

1. Introduction

In 2016, Sustainable Development Goals of the 2030 Agenda for Sustainable Development adopted by world leaders took effect (United Nations, 2017). Improving eco-efficiency is considered to be an essential approach for easily reaching sustainable development goals (Chen et al., 2017). In this context, the United Nations Industry and Development Organization (UNIDO) identified eco-efficiency as one of the major strategic elements in its work on sustainability (UNIDO, 2012). The concept of eco-efficiency was first defined by Schaltegger and Sturm (1989) as the ratio between amount of environmental impact and value added. In other words, eco-efficiency entails producing more goods and services with fewer resources, and with less environmental impacts (Beltrán-Esteve et al., 2017).

Wastewater treatment is essential for protecting human health and environmental sustainability (IOC/UNESCO, 2011). A wastewater treatment plant (WWTP) is a special type of productive unit that both uses energy and materials to remove pollutants from wastewater and discharges pollutants (suspended solids, organic matter, nutrients) into the environment (Ren and Liang, 2017). The ability to quantify eco-efficiency of WWTPs is essential for determining success, identify and track trends, prioritize actions, and identify areas for improvement. Hence, in recent years, a series of research studies have been aimed at assessing the eco-efficiency of WWTPs (Molinos-Senante et al., 2016a). However, given the multidimensionality of the eco-efficiency concept, developing assessment protocols is a complex task.

Life-cycle assessment (LCA), data envelopment analysis (DEA) and a combination of them (LCA + DEA) have been conventionally employed to evaluate the eco-efficiency of WWTPs (Larrey-Lassalle et al., 2017; Laitinen et al., 2017; Lorenzo-Toja et al., 2017; Guerrini et al., 2017). LCA is a robust method used to quantify the global environmental impact of a functional unit (Bidstrup, 2015) and therefore, LCA quantifies environmental impacts of WWTPs in much more detail than DEA. However, LCA does not consider economic variables in its assessment,

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https://doi.org/10.1016/j.eiar.2017.11.007
Received 2 August 2017; Received in revised form 24 November 2017; Accepted 28 November 2017
Available online 06 December 2017
0195-9255/

which is an important shortcoming. It should be noted that in the term eco-efficiency, the prefix "eco" represents both ecological and economic performance (Yin et al., 2014). In contrast, DEA provides a synthetic performance index that integrates multiple inputs and multiple outputs (economic and environmental) (Cooper et al., 2007). DEA method presents an additional and fundamental advantage: it enables to integrate environmental impacts in the eco-efficiency assessment as undesirable outputs. By contrast, in LCA and LCA + DEA they are integrated in the assessment as inputs. However, several papers have evidenced the limitations of this approach (Pérez et al., 2017) since treating undesirable outputs as inputs does not reflect the real production process. Hence, DEA is superior to LCA in evaluating and comparing the eco-efficiency of WWTPs (Dong et al., 2017).

Given the advantageous features of the DEA approach, several DEA models have been used to evaluate the eco-efficiency of WWTPs, by considering economic variables as inputs and pollutant-removal efficiency as outputs (e.g. Hernández-Sancho et al., 2011; Sala-Garrido et al., 2012; Guerrini et al., 2015; Tomei et al., 2016; Dong et al., 2017). Within the framework of DEA, eco-efficiency can be evaluated by incorporating environmental impacts as undesirable outputs generated by the productive process (Luptacik, 2000). Eco-efficiency evaluations of WWTPs integrate three components into a synthetic index, namely: i) desirable outputs (pollutants removal efficiency), which should maximized; ii) inputs (economic costs) to be minimized; and, iii) undesirable outputs (environmental impacts), which should minimized (Liu et al., 2017). The great advantage of using this approach is that the index holistically integrates the three dimensions of eco-efficiency, specifically service value, resource consumption, and environmental impacts (Ji, 2013).

The integration of environmental impacts, as undesirable outputs, has been widely considered in eco-efficiency assessments for several types of production systems, such as cement firms (Oggioni et al., 2017), agricultural units (Pan and Ying, 2013), coal-fired power plants (Liu et al., 2017), tourism destinations (Peng et al., 2017), among others. However, in the framework of WWTPs, only Molinos-Senante et al. (2016a) integrated an environmental impact (greenhouse gas (GHG) emissions) as an undesirable output when evaluating eco-efficiency. In this integration, they employed the weighted Russell directional distance model (WRDDM). This non-radial DEA model differs from radial DEA models in that it allows one to obtain an eco-efficiency index for each input and output (both desirable and undesirable) involved in the analysis, in addition to generating a global efficiency index (Wei et al., 2013). In spite of the great use of previous studies evaluating the eco-efficiency of WWTPs (both integrating and not environmental impacts as undesirable outputs), they provided a static assessment. In other words, they assessed the performance of WWTPs for a given moment of time, without regard to potential changes over time within the WWTPs. Thus, this approach is purely static and cannot account for changes in the performance of WWTPs. However, in order to better support the decision-making process, information about temporal dynamics of eco-efficiencies is essential. Being able to assess changes in eco-productivity over time not only allows one to compute the eco-efficiency of a WWTP for any given time period, but it allows one to compare the eco-efficiency among WWTPs (Al-Refaie et al., 2016). By quantifying eco-productivity change over time, one can determine whether the eco-efficiency of units (WWTPs in this study) has improved or worsened over a given period of time (Mahlberg et al., 2011). The assessment of eco-productivity change involves extending the notion of eco-efficiency to an interporal setting (Mahlberg et al., 2011).

Despite the usefulness of evaluating the dynamic eco-efficiency of WWTPs, no studies have been published dealing with this issue. To overcome this gap in the literature, the main objective of this paper was to evaluate changes through time in the eco-productivity of WWTPs using the dynamic WRDDM. This model allowed us to quantify contributions of inputs and outputs (both desirable and undesirable) to changes in eco-productivity and its drivers (i.e., relative to changes in efficiency and changes in technology). This paper pioneers the use of the WRDDM approach by extending static eco-efficiency analysis to an inter-temporal approach. Moreover, our approach is the first attempt at evaluating the eco-productivity (eco-efficiency over time) of WWTPs by incorporating GHG emissions as undesirable outputs.

From a policy and management perspective, evaluating dynamic eco-efficiency (i.e., change in eco-productivity) of WWTPs is essential for developing long-term policies aimed at promoting sustainable wastewater treatment. Computing the effects of inputs and outputs on overall change in eco-productivity (and its drivers) provides valuable information for policy makers. For example, it allows policy-makers to identify whether changes in eco-productivity of WWTPs are driven by changes in economic costs, efficiencies in removing pollutants, and/or GHG emissions. This information is of value because it can be used to support policies and managerial strategies that improve the eco-efficiency of WWTPs. Quantifying changes in the eco-productivity over time is also very useful for evaluating the successes/failures of WWTP management practices and wastewater treatment policies adopted by water regulators.

2. Eco-productivity change and DEA methodology

Changes in eco-productivity of WWTPs were estimated by applying an approach proposed by Fujii et al. (2014). This approach is an extension of the WRDDM approach introduced by Chen et al. (2010) and Barros et al. (2012), which integrates a temporal dimension to conventional eco-efficiency assessments. It quantifies both the change in total factor eco-productivity (TFEPC) and the relative contributions of inputs and outputs (both desirable and undesirable) to the change (Fujii et al., 2017).

The dynamic WRDDM is based on a directional distance function combined with a non-parametric DEA approach (Molinos-Senante et al., 2016b). Considering that units (WWTPs in this study) use a vector of inputs ($x \in \Re_+^{\ N}$) to produce a vector of desirable ($y \in \Re_+^{\ M}$) and undesirable ($b \in \Re_+^{\ J}$) outputs, the directional distance function, as defined by Yang and Zhang (2016) is:

$$D(x, y, b; g) = \sup\{\rho\colon (x - \rho g_x, y + \rho g_y, b - \rho g_b) \in T\} \tag{1}$$

where $g = (g_x, g_y, g_b)$ is the vector that determines the direction in which inputs, desirable outputs, and undesirable outputs are scaled; ρ is the distance between the unit, (a WWTP in this study) and the efficient frontier.

$D(x, y, b; g)$ represents production inefficiency and so $D(x, y, b; g) = 0$ means that the unit is on the frontier, and therefore, is efficient. By contrast, if $D(x, y, b; g) > 0$, the unit is inefficient and has room to improve its performance (Zhou et al., 2014). Unlike the Shephard distance function, the directional distance function gives both the expansion (in desirable outputs) and contraction (in inputs and undesirable outputs) (Zelenyuk, 2014).

The Malmquist productivity index (MPI) and the Luenberger productivity indicator (LPI) are two widely-used models employed to evaluate changes in efficiency over time following a non-parametric approach. Nevertheless, Boussemart et al. (2003) determined that the LPI encompasses the MPI. Given that the LPI is a generalization of the MPI, in this study changes in eco-productivity of the WWTP were assessed by employing the LPI.

Based on the WRDDM, the TFEPC or the eco-productivity change between time t and $t + 1$ for the k unit (a WWTP in this study) is described as follows (Fujii et al., 2014):

$$\begin{aligned} TFEPC_t^{t+1} = \frac{1}{2}\{&D^{t+1}(x_k^t, y_k^t, b_k^t) - D^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) + D^t(x_k^t, y_k^t, b_k^t) \\ &- D^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})\} \end{aligned} \tag{2}$$

where $x_k^{\ t}$ is the input for year t, $x_k^{\ t\ +\ 1}$ is the input for year $t + 1$, $y_k^{\ t}$ is the desirable output for year t, y_k^{t+1} is the desirable output for year $t+1$, b_k^t is the undesirable output for year t, b_k^{t+1} is the undesirable output for year $t+1$. $D^t(x_k^t, y_k^t, b_k^t)$ is the inefficiency score of year t based on the frontier curve in year t. Analogously, $D^{t+1}(x_k^t, y_k^t, b_k^t)$ is the inefficiency score of year t based on the frontier curve in year $t+1$. Also, the similar for $D^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$ and $D^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$. The TFEPC index indicates the change in eco-productivity relative to the benchmark (reference) year.

Hereinafter, the following notation has been adopted for simplicity:

$$D_t^{t+1} = D^{t+1}(x_k^t, y_k^t, b_k^t)$$

$$D_{t+1}^{t+1} = D^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$$

$$D_t^t = D^t(x_k^t, y_k^t, b_k^t)$$

$$D_{t+1}^t = D^t(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})$$

The TFEPC can be broken into two components or drivers of eco-productivity change, specifically, eco-technical change (ETC) and eco-efficiency change (EFC). ETC measures the change in the efficient frontier between two time periods (Molinos-Senante and Sala-Garrido, 2015). In other words, ETC explains the shift in the efficient frontier across years. The EFC, also known as the catch-up index, reveals the capacity of a facility to be managed at the efficient frontier. Therefore, positive values of EFC are mainly attributed to managerial improvements in efficiency (Simoes and Marques, 2012).

The TFEPC is defined as:

$$TFEPC_t^{t+1} = ETC_t^{t+1} + EFC_t^{t+1} \tag{3}$$

such that,

$$ETC_t^{t+1} = \frac{1}{2}\{D_t^{t+1} + D_{t+1}^{t+1} - D_t^t - D_{t+1}^t\} \tag{4}$$

$$EFC_t^{t+1} = D_t^t - D_{t+1}^{t+1} \tag{5}$$

TFEPC and its components (ETC and EFC) are interpreted as follows: (i) a TFEPC > 0 indicates an improvement in eco-productivity; (ii) a TFEPC < 0 means a worsening of eco-productivity; and, (iii) a TFEPC $= 0$ indicates that eco-productivity has not changed.

TFEPC can be disaggregated using the contribution effects for inefficiency of inputs and desirable and undesirable outputs, which are as follows (see Fujii et al., 2014):

$$D(x_k^t, y_k^t, b_k^t) = \max\left(\frac{1}{N}\sum_{n=1}^{N}\beta_n^{k\prime} + \frac{1}{M}\sum_{m=1}^{M}\beta_m^{k\prime} + \frac{1}{J}\sum_{j=1}^{J}\beta_j^{k\prime}\right) = D_x(x_k^t, y_k^t, b_k^t) + D_y(x_k^t, y_k^t, b_k^t) + D_b(x_k^t, y_k^t, b_k^t) \tag{6}$$

where N, M and J is the total number of inputs, desirable outputs and undesirable outputs involved in eco-efficiency assessment. $\beta_n^{k\prime}$, $\beta_m^{k\prime}$ and $\beta_j^{k\prime}$ are the individual inefficiency scores for inputs, desirable outputs and undesirable outputs, respectively. $D_x(x_k^t, y_k^t, b_k^t)$ is the contribution of input variables in the inefficiency index. $D_y(x_k^t, y_k^t, b_k^t)$ is the contribution of desirable output variables in the inefficiency index. $D_b(x_k^t, y_k^t, b_k^t)$ is the contribution of undesirable output variables in the inefficiency index.

From Eqs. (2) and (6), TFEPC is decomposed as follows (Fujii et al., 2015):

$$TFPC_t^{t+1} = TFEPC_{t,x}^{t+1} + TFEPC_{t,y}^{t+1} + TFEPC_{t,b}^{t+1} \tag{7}$$

where:

$TFEPC_{t,x}^{t+1}$ is the contribution of input variables relative to eco-productivity change; $TFEPC_{t,y}^{t+1}$ is the contribution of desirable output variables for eco-productivity change; $TFEPC_{t,b}^{t+1}$ is the contribution of undesirable output variables for eco-productivity change.

Because the WRDDM assesses the contribution of each variable to TFEPC, the ETC and EFC indicators can also be decomposed as follows:

$$ETC_t^{t+1} = ETC_{t,x}^{t+1} + ETC_{t,y}^{t+1} + ETC_{t,b}^{t+1} \tag{8}$$

$$EFC_t^{t+1} = EFC_{t,x}^{t+1} + EFC_{t,y}^{t+1} + EFC_{t,b}^{t+1} \tag{9}$$

The methodological approach used in this study allows one to obtain an eco-productivity change index for inputs, desirable outputs, and undesirable outputs. This approach is very relevant for WWTP managers and policy makers that want to develop long-term plans and implement specific measures to improve the performance of WWTPs over time.

3. Eco-productivity of WWTS: data and variables

Thirty WWTPs in Spain were sampled over the 2014 and 2016 time period. These WWTPs were operated jointly by the provincial council and the local council where each facility was located. The assessed WWTPs featured three different secondary treatment technologies, specifically a conventional activated sludge (CAS) system, rotating biological contactors (RBC), and trickling filters (TF). The 30 plants mainly removed suspended solids (SS) and organic matter from wastewater because they had no ability to remove nutrients (nitrogen and phosphorus). The WWTPs plants were all considered to be small, ranging in treatment capacity from 22,000 m^3/year to approximately 550,000 m^3/year. The selection of the variables we used to assess the dynamic eco-efficiency of the WWTPs was based on previous studies (Sala-Garrido et al., 2012; Castellet and Molinos-Senante, 2016; Dong et al., 2017) and in the broader concept of eco-efficiency, which integrates three concepts, specifically, the value of services provided, the amount of resources consumed, and environmental impacts (Ji, 2013). When evaluating performance, these concepts are comprised of desirable outputs, inputs, and undesirable outputs. The main function of WWTPs is to reduce negative impacts to water bodies by reducing pollutants discharged into them. Therefore, variables identified as desirable outputs should be pollutants removed from wastewater. Based on the operational characteristics of the WWTPs evaluated in our study, the removal of SS and organic matter (measured as chemical organic demand (COD)) were selected as desirable outputs. Furthermore, both pollutants were expressed as kilograms per year in order to incorporate influent and effluent characteristics into our assessment.

Inputs examined in the assessment should reflect resource consumption by WWTPs. Accordingly, four inputs were considered: i) staff costs, which includes salaries and social charges of plant employees, which represent around 30% of the total operating costs of WWTPs (Molinos-Senante et al., 2010) and so is important to include them in performance studies; ii) maintenance costs, that includes equipment and machinery maintenance and replacement; iii) waste costs, which include costs related to waste and sludge management; and, iv) other costs, which incorporate various other types of costs, such as reagent costs, laboratory costs, office supplies, and administration.

In context of the water-energy nexus, the contribution of WWTPs to the urban carbon footprint is relevant (Roefs et al., 2017). In recent years, energy consumed by WWTPs has risen markedly, due to an increase in the volume of wastewater treated and the implementation of new processes to improve effluent water quality (Gu et al., 2016). Because energy consumption is an important parameter to consider when examining environmental impacts associated with WWTP operation, this study focused on the effects of WWTP operation on climate change. In particular, indirect greenhouse gas (GHG) emissions (expressed as kilograms of CO_2 equivalent) was chosen as an undesirable output (Molinos-Senante et al., 2016a) produced by WWTPs. The estimates of indirect GHG emissions were based on the energy demand of the WWTPs evaluated, the Spanish electrical production mix for 2014 and 2016, and potential 100-year global warming coefficients. GHG emissions (per kWh of electricity produced) averaged 372 g CO_2-eq in 2014 and 308 g CO_2-eq in 2016 (EU, 2014). Electrical energy production also involves the emission of other pollutants such as SO_2, NO_x and particulate matter. However, in this study these pollutants could not be integrated in the eco-productivity assessment as undesirable outputs due to data availability restrictions.

The operation of WWTPs also involved direct GHG emissions, which were mostly biogenic and therefore, did not contribute to global warming (Wang, 2010). CH_4 is the main GHG gas produced when processing sewage sludge (Dong et al., 2017). In large plants, CH_4 is collected and used as an energy source (Meneses et al., 2015). However, the 30 facilities evaluated in this study were too small to treat the sludge anaerobically or to monitor CH_4 emissions.

N_2O is another GHG that also contributes to global warming in WWTPs. Its contribution is notable because its global warming potential (over a 100-year period) is 298 times higher than CO_2 (IPCC, 2014). The amount of direct N_2O emitted is determined by both the amount of nitrogen removed from treated water and the amount discharged with treated water (Dong et al., 2017). However, according the effluent requirements outlined by European Directive 91/271/EC, it is not compulsory to remove nitrogen from effluents discharged to non-sensitive waters. Because none of the WWTPs we studied discharged into sensitive waters, none of the WWTPs we evaluated were required to remove nitrogen nor monitor its concentration in their effluents. Hence, it was impossible to estimate direct N_2O emissions from the WWTPs we studied. It is a limitation of the empirical application carried out in this study that should be considered in future research. N_2O is a by-product and intermediate product emitted during the biological denitrification and nitrification processes. Several factors such as dissolved oxygen, pH, and the carbon-nitrogen ratio influence its generation. Thus, usually emissions factors are not estimated through stoichiometric equations but based on empirical statistics. Yang (2013) reported for conventional nitrification and denitrification process an average emission factor of 0.035 kg N_2O-N/kg N removal. Regarding the natural N_2O emissions from water treated, the IPCC (2006) estimated an emission factor of 0.005 kg N_2O-N/kg N. For future empirical applications if information about total nitrogen concentrations of the WWTP influent and effluent is available both sources of direct N_2O emissions (nitrogen removal and water treated) should be integrated in the eco-productivity assessment.

Descriptive statistics of the variables used in this study are summarized in Table 1. Operational and maintenance costs increased from 2014 to 2016. Specifically, staff costs, waste management costs, and maintenance costs rose by 25%, 34% and 8%, respectively. In contrast, other costs decreased by 34%. Between 2014 and 2016, model outputs (SS and COD removed) remained almost constant. Table 1 also shows that over the period analysed, indirect GHG emissions were reduced, on average, by 29%. Two factors contributed to this improvement in GHG emissions. First, the Spanish electrical production mix reduced GHG emissions from 0.372 to 0.308 kg CO_2eq. Second, average energy consumption in the WWTPs we evaluated decreased sharply from 0.278 to 0.237 kWh/m^3.

4. Results and discussion

Our assessment of changes in eco-productivity is based on an efficient frontier method, such as the dynamic WRDDM, allowed us to estimate changes for each WWTP facility. This benchmark approach is very relevant, because it enabled us to identify the best WWTPs, which then could be used as a basis of reference for the other WWTPs.

Fig. 1 shows the TFEPC for the 30 WWTPs we assessed from 2014 to 2016 and Fig. 2 illustrates the contribution of inputs, desirable outputs, and undesirable outputs. This illustrates that 17 of 30 WWTPs (57%) improved their eco-productivities from 2014 to 2016 and that the indices related to improvement are extremely variable, ranging from 0.1 to 1.3. In nine of the 17 WWTPs, the improvement was due to improvements in all model components (i.e., operational costs declined, pollutants were removed more efficiently, and indirect GHG emissions were reduced). However, six of the 17 WWTPs that improved their eco-productivities, also reduced their inputs. This finding suggests that the positive behaviour regarding desirable outputs and/or undesirable output generation compensated for reductions in operational costs. For two of 17 WWTPs, changes in GHG emissions contributed negatively to eco-productivity changes. The fact that eight of the 17 WWTPs that improved their TFEPC scores showed a reduction in one or two of their eco-productivity components, reveals that the lower-scoring WWTPs can improve their eco-efficiencies relative to the best- performing WWTPs.

13 of 30 WWTPs (43%) declined in their eco-productivities between 2014 and 2016. While some facilities showed a small reduction in their eco-productivities (− 0.06), others experienced dramatic reductions (− 0.89). (Only in the three worst-performing plants did changes in inputs, desirable outputs, and undesirable outputs contribute negatively to their reductions in eco-productivities.) Within this group of 13 WWTPs with reductions in eco-productivity, eight plants showed an increase in pollutant-removal efficiency. However, operational costs and GHG emissions contributed negatively to eco-productivity scores for 10 of the 13 facilities. This means that the negative performance of these plants, relative to inputs (costs) and the generation of undesirable outputs, were not compensated by improvements in their production of desirable outputs, leading to a reduction in their eco-productivities. This finding suggests that although these WWTPs incorporated technological improvements that provided additional beneficial services, these improvements also increased resource consumption and caused negative environmental impacts, resulting in a reduction in their eco-productivities.

Fig. 2 shows the importance of examining the contribution of individual variables to changes in eco-productivity scores. For example, the WWTP20 had the worst performance relative to operating costs. However, it performed relative well to both GHG emissions and pollutant removal efficiency, which together increased its eco-productivity. From a managerial perspective, this plant could improve its eco-productivity further by concentrating on reducing its operating costs. Similar analyses could be made for the remaining plants. This

Table 1
Sample description.

		Staff costs (€/year)	Waste management costs (€/year)	Maintenance costs (€/year)	Other costs (€/year)	Organic matter removed (kg COD/year)	Suspended solids removed (kg COD/year)	Greenhouse gas (kg CO_2eq/year)
2014	Average	13,680	1671	1846	4886	418	161	22,718
	SD	11,313	1913	1855	1260	226	83	30,515
	Minimum	1347	100	90	3347	82	30	407
	Maximum	48,658	6704	5780	8170	1108	388	111,667
2016	Average	17,167	2240	2000	3215	423	161	16,029
	SD	14,198	2458	2078	1003	234	68	18,156
	Minimum	1691	7	73	2236	93	33	160
	Maximum	61,063	9733	10,107	6663	1112	387	64,475

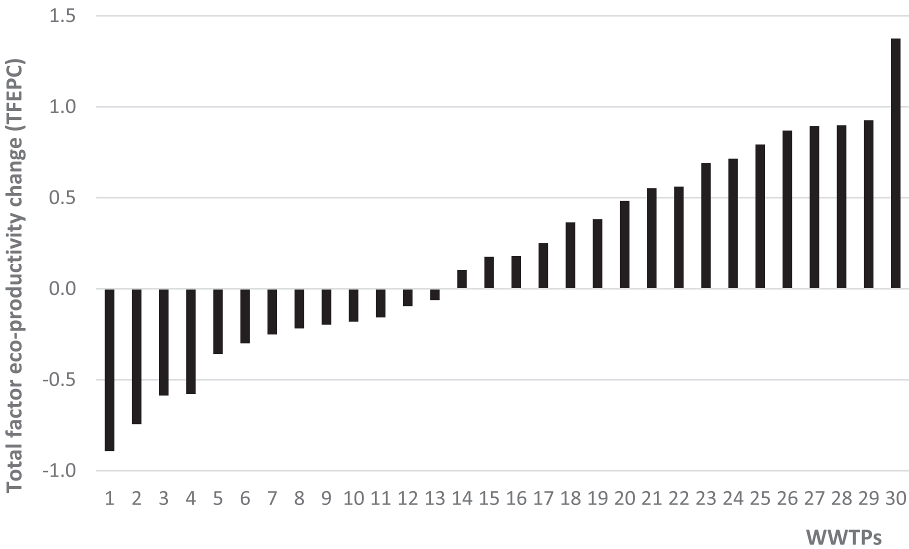

Fig. 1. Total factor eco-productivity change from 2014 to 2016 for wastewater treatment plants.

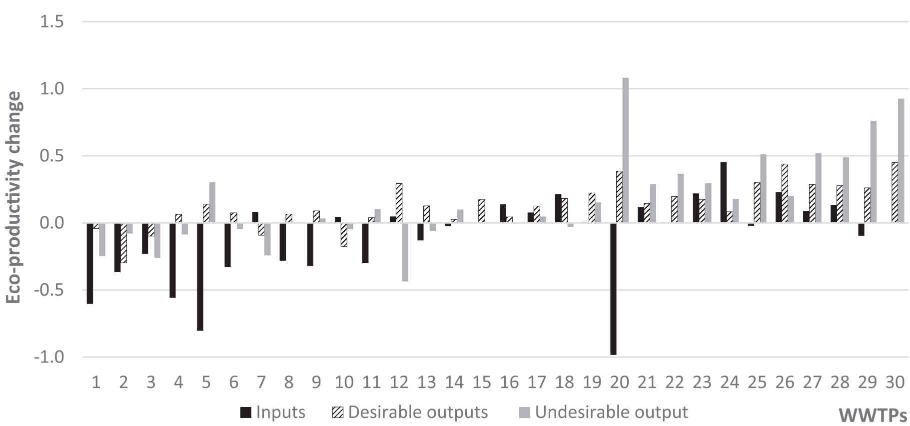

Fig. 2. Eco-productivity change of inputs, desirable outputs and undesirable outputs from 2014 to 2016 for wastewater treatment plants.

example illustrates the importance of identifying the drivers of eco-productivity change in order to support decision making.

In order to gain a better understanding of the factors that drive eco-productivity changes in WWTPs, Table 2 shows values of TFEPC, ETC, and EFC for the 30 WWTPs we evaluated. (To ease in their interpretation, values indicating a negative change were shaded as grey boxes.) Within the group that declined in eco-productivity over the study period, six of 13 WWTPs (46%) exhibit a positive shift of the efficient frontier (i.e., their ETC improved). In fact, the three WWTPs with the worst TFEPC increased their ETC. This means that these WWTPs declined in eco-productivity because they failed to adopt notable managerial improvements. In contrast, only one of 13 facilities showed a positive value in its catch-up index. Moreover, Table 2 shows that in five WWTPs, eco-efficiency remained constant. In other words, they did not incorporate any managerial improvements during the period evaluated. Our results illustrate that, with the exception of the WWTP 5 that improved its EFC, a reduction in eco-efficiency was the main driver of declines in eco-productivity.

In contrast to the 13 WWTPs that declined in eco-productivity, 17 of the 30 plants we analysed exhibited increases in their TFEPC scores. This means that they produced more service value using fewer resources and/or reduced their environmental impacts. For nine of the 17 plants, both EFC and ETC indices increased. This means that these WWTPs adopted substantial managerial improvements, which allowed them to approach the efficient frontier. For the remaining facilities (eight of 17) one driver of eco-productivity change was negative. This means that although the eco-productivity of these WWTPs improved from 2014 to 2016, they had potential for additional eco-productivity improvements if they were to adopt better managerial practices or long-term planning.

To develop policies aimed at improving ETC and EFC, it is important to identify which variables WWTP managers should improve upon. Figs. 3 and 4 show the contribution of operating costs (inputs), pollutants removed (desirable outputs), and GHG emissions (undesirable outputs) to ETC and EFC values. Fig. 3 illustrates that operating cost was the main factor responsible for the negative shift in the efficient frontier in that 21 of 30 WWTPs (70%) declined in performance relative to cost. By contrast, efficiency in the removal of pollutants contributed markedly to the positive shifts in the efficient frontier, because only one facility declined relative to this variable. Finally, the contribution of GHG emissions to ETC scores was moderate because it was negative for nine WWTPs and positive for the remaining 21 plants. These results indicate that to achieve cost reductions, water regulators and WWTP managers should implement long-term planning policies and measures that focus on more efficient use of energy and provide better protocols for reducing costs of reagents and other materials.

Fig. 4 shows that six of the 30 WWTPs (20%) we studied (WWTPs 9, 11, 15, 17, 18, 24) did not experienced changes in eco-efficiency from 2014 to 2016. This means that their positions with respect to the efficient frontier did not change during that period and it was for inputs, desirable outputs and undesirable outputs. The disintegration of the EFC for inputs, desirable outputs and undesirable output evidences that for inputs (operational costs), 10 of 30 plants (30%) presented a retardation of the EFC. This means that these WWTPs increased their

Table 2
Eco-technical change (ETC), eco-efficiency change (EEC) and total factor eco-productivity change (TFEPC) at wastewater treatment level.

WWTP	ETC	EFC	TFEPC
1	0.308	− 1.200	− 0.892
2	0.679	− 1.423	− 0.744
3	0.587	− 1.174	− 0.587
4	− 0.579	0.000	− 0.579
5	− 1.363	1.004	− 0.359
6	0.044	− 0.344	− 0.300
	0.164	− 0.415	− 0.251
8	− 0.060	− 0.157	− 0.218
9	− 0.198	0.000	− 0.198
10	− 0.181	0.000	− 0.181
11	0.096	− 0.254	− 0.158
12	− 0.095	0.000	− 0.095
13	− 0.062	0.000	− 0.062
14	0.195	− 0.092	0.103
15	0.502	− 0.327	0.176
16	0.180	0.000	0.180
17	0.174	0.077	0.251
18	− 0.258	0.622	0.365
19	0.770	− 0.388	0.382
20	− 0.184	0.667	0.483
21	− 0.399	0.953	0.553
22	0.463	0.098	0.561
23	0.320	0.370	0.690
24	0.008	0.707	0.715
25	0.572	0.220	0.793
26	− 0.181	1.051	0.870
27	0.443	0.451	0.894
28	0.566	0.333	0.899
29	− 0.600	1.526	0.927
30	0.360	1.015	1.375

operating costs, causing them to move away from the efficient frontier. Most of the treatment plants showed improvement in their performances regarding pollutant removal, given that for 14 of the 30 WWTPs (47%), desirable outputs provided positive contributions to EFC scores. In the case of GHG, the EFC indicator showed a similar behaviour to ETC because, for some treatment plants, this variable contributed positively to the score, whereas for other plants, it contributed negatively to scores. For the WWTPS we evaluated, none of the variables used in the assessment showed any more relevance to EFC scores than other variables. This is because differences in EFC scores can be attributed to managerial differences, which varied among WWTPs. Therefore, universal recommendations useful for improving eco-efficiency cannot be made for plants with low EFC scores. Each plant is unique in its management approach and so each should identify the factors that negatively impact its particular eco-efficiency scores, which provide insight into managerial measures that can improve the situation.

The empirical approach carried out in this study illustrates the importance of using quantitative approaches, such as the dynamic WRDDM, to evaluate changes in the eco-productivity of WWTPs. This model allows one to identify the various drivers of eco-productivity and the factors involved, specifically costs, pollutant-removal efficiency, and GHG emissions, all of which WWTPs managers should address to improve the performance of WWTPs over time and thus contribute to their long-term sustainability.

5. Conclusions

In the context of urban sustainability, the eco-efficiency of WWTPs has been identified as one of the major strategic elements in need of addressing. Thus, in recent years, a series of research studies have focused on assessing the eco-efficiency of WWTPs. However, previous studies were inadequate in extending the static eco-efficiency analysis to an intertemporal setting; that is, changes over time were not assessed. The assessment of TFEPC allow managers to identify which components of EFC and ETC (operational costs, pollutant-removal efficiency, and/or environmental impacts) were mainly responsible for eco-productivity change. Having information about the both issues (change with time and ability to pinpoint problems) is essential for developing management actions and policies that promote the long-term sustainability of WWTPs.

In order to overcome the above-described limitations of conventional approaches for quantifying eco-efficiency, this paper evaluated changes in the eco-productivity of WWTPs using the dynamic WRDDM approach. For each treatment plant, four eco-productivity indices were estimated: i) change over time in total eco-productivity; ii) change over time in eco-productivity relative to inputs; iii) change over time in eco-productivity relative to efficiency or pollutant removal; and iv) change over time in eco-productivity relative to GHG emissions. This exhaustive analysis of eco-productivity was undertaken to gain a better understanding of the behaviour of WWTPs through time.

Our main findings are as follows: i) half of the WWTPs improved their eco-productivity; ii) some of the facilities that improved their eco-productivity still had potential to improve further; iii) the reduction in eco-productivity was due mainly to operating costs and GHG emissions. In contrast, efficiency of pollutant removal improved in some of the WWTPs that exhibited a reduction in eco-productivity; iv) for most of the WWTPs, a decline in eco-efficiency was the main driver of reductions in eco-productivity; and, v) operating costs were mainly responsible of negative shifts in the efficient frontier, which was in contrast to pollutant removal efficiency (which contributed moderately and positively to eco-productivity).

From a managerial and policy perspective, the methods and results of this study are of universal application. First, we showed how important it is to evaluate eco-efficiency through time and not just at a given moment in time. Second, determining the contribution of specific drivers (inputs, desirable outputs, and undesirable outputs) to changes in eco-productivity could enable WWTP managers to adopt specific

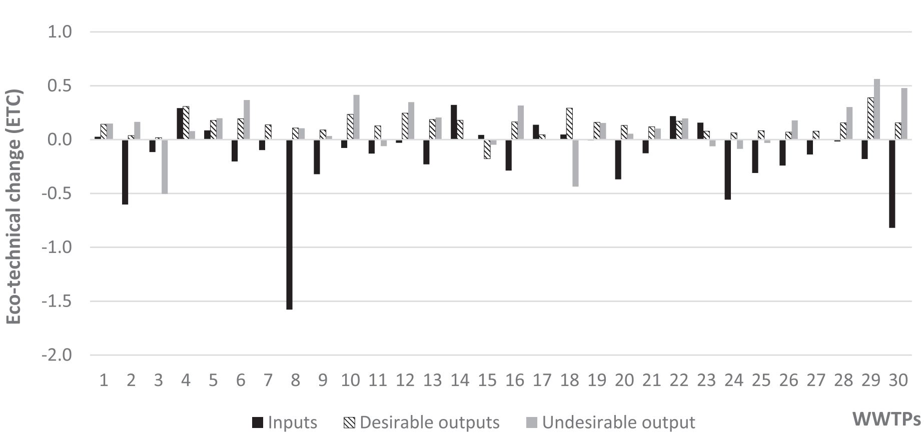

Fig. 3. Eco-technical change of inputs, desirable outputs and undesirable outputs from 2014 to 2016 for wastewater treatment plants.

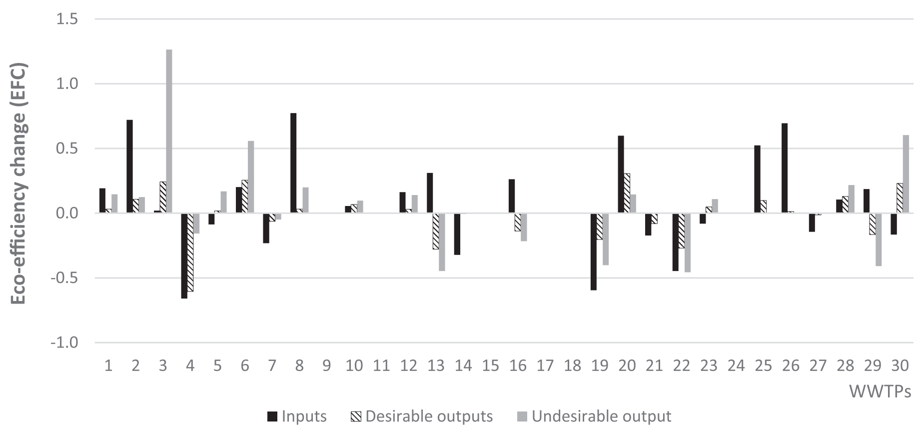

Fig. 4. Eco-efficiency change of inputs, desirable outputs and undesirable outputs from 2014 to 2016 for wastewater treatment plants.

management actions (at scale of individual WWTPs) to improve eco-productivity. Third, the benchmarking exercise carried out in this study might be very useful for wastewater authorities to use for defining eco-productivity improvement goals. Fourth, in countries where water and sanitation is regulated, wastewater authorities should provide incentives to WWTP companies to implement policies and measures that improve the eco-productivity of WWTPs over time. This approach would provide positive benefits not only for WWTP operators, but also for citizens, because it could substantially improve urban sustainability.

One important challenge to improve the eco-efficiency of WWTPs is to transfer scientific research to practitioners (WWTP operators) and decision-makers (water regulators). It involves interactions between scientists and stakeholders at national, regional and local levels, also engagement with citizens. To achieve this objective several initiatives can be implemented such as the development of Policy and Practice Reports which contribute to foresee policy interventions and community accompaniment opportunities. Active citizenship and city engagement programmes are also useful tools to empower population since citizens and local organizations are important potential agents of change for generating more sustainable settlements (CEDEUS, 2017).

Acknowledgments

This work was supported by the Spanish Ministry of Education [ECO2016-76567-C4-4-R]; the Junta de Andalucía [SEJ417]; and Conicyt [Fondecyt (11160031)].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2017.11.007.

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