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A composite indicator index as a proxy for measuring the quality of water supply as perceived by users for urban water services

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A R T I C L E I N F O

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A B S T R A C T

The objective of this study is to develop a composite indicator (CI) to measure the quality of water supply based on the variables that are considered to affect users' perceptions of water supply quality. The proposed CI includes six relevant aspects that determine users' perceptions of water supply quality (network quality, water quality, water price, complaints, inconvenience caused by upgrading the network, and continuity of service) in a simple, economical, and objective way, using multi-criteria decision analysis (MCDA) with weights based on data envelopment analysis (DEA). The CI was applied to 32 municipalities in the metropolitan area of Valencia (Spain). The results show the high quality of the water supply service in this area. The use of this CI to measure the quality of the water supply service may prove useful for public institutions and managers of urban water supply, giving them an instrument to improve the management, efficiency, and quality of the water services they provide.

1. Introduction

According to the United Nations, water is "a limited natural resource and a public good fundamental for life and health", while "the right to safe and clean drinking water and sanitation is a human right that is essential for the full enjoyment of the right to life and all human rights" (United Nations General Assembly, 2010) such as health, food, and hygiene. For this reason, in 2010, the United Nations General Assembly recognized the right to water and sanitation as a human right (Salman, 2014) within the economic, social, and cultural rights category. Achieving this human right to water and sanitation means ensuring the availability, accessibility, quality, safety, and affordability of water to meet the requirements of acceptability, dignity, and privacy (Meier et al., 2014; Heller, 2015).

In addition to the idea that access to water is a basic human need, the influence of water quality on quality of life is also relevant. Quality of life is an important multi-dimensional concept that has gained ground in recent years. Quality of life can refer to both the specific attributes of people (such as health and education) and the conditions of the environment to which they relate, including the provision of public service infrastructures (Reig, 2015). In this sense, water quality affects people's quality of life (Papageorgiou, 1976; Myers, 1987; McMahon, 2002; Jerome and Pius, 2010).

Drinking water quality is largely influenced by the quality of the source water (Aziz, 2005) and is associated with the conditions of the water supply networks (Kaplan et al., 2011). This study only addresses water supply, which is the phase of the urban water cycle from water catchment to users' taps, including drinking water treatment and water distribution. The phase prior to water abstraction and the phase of sanitation and wastewater treatment to return the water to the environment are not the subject of this study.

In Spain, drinking water supply is one of the most important local services provided by all municipalities, regardless of their population size. Water supply is listed in Article 26.1 of Law 7/1985 (Regulation of Competences of Local Authorities) as an essential public utility service (Benito et al., 2019). The primary responsibility of policy makers is to ensure sufficient water resources exist to supply urban populations, but the secondary aim of welfare enhancement should not be forgotten (Byrnes et al., 2010).

For all these reasons, indicators have been designed to assess the availability, quality, accessibility, and affordability of water supply (García-Valiñas et al., 2010a; Hutton, 2012; Kayser et al., 2013). The acceptability of the service has recently been used as an indicator (Flores-Baquero et al., 2013). To control the quality of the service and

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improve its management, water utilities use different indicators combining information about different managerial, environmental, financial, and, more recently, social aspects related to water operations. However, this set of indicators is difficult to interpret because it does not offer a holistic view, given that the indicators do not reflect a measure of general performance (Cherchye et al., 2006).

The need for managers and public officials to monitor user satisfaction has motivated attempts at measuring users' perceptions of water supply quality. Traditionally, surveying has been the most widely used method to analyze these perceptions. Personal, telephone, and self-report questionnaires have been used for this purpose. The widespread use of surveys as a research procedure has several advantages. For example, surveys can be applied on a massive scale and can yield data on a wide range of questions (Martínez-Medino and Galán-González, 2004; Arroyo-Menéndez and Sábada-Rodríguez, 2012). These data can then be processed quickly and efficiently. Surveys have been used in several articles to gather users' opinions about the water supply service. Specifically, they have been used in studies of water quality (Burlingame et al., 2017; Ortiz-Gómez et al., 2019; Delpla et al., 2020; Weisner et al., 2020) and the consumption preferences of users that lead them to choose tap water or bottled water (Etale et al., 2018; Qian, 2018; Geerts et al., 2020).

Despite this widespread use of surveys as a data gathering procedure, they are costly and introduce a high degree of subjectivity due to difficulties associated with survey design, type of survey, application method, and statistical method (Casas-Anguita et al., 2003; Martínez-Medino and Galán-Gonzalez, 2004; Kvale, 2012; Arroyo-Menéndez and Sábada-Rodríguez, 2012). To overcome these difficulties, a common approach is to aggregate variables into a single indicator, called a composite indicator (CI) [also called Composite Index in the literature]. A CI is a method of aggregating variables that offers a valuable tool for measuring, monitoring, comparing, and evaluating user opinion, analyzing policies, communicating public information, and so forth. The use of CIs is internationally established (Joint Research Centre, 2008; Hatefi and Torabi, 2010; 2018). The main advantage of a CI over other methods is that it synthesizes the evaluation of a complex, multi-dimensional phenomenon, enabling its interpretation by service managers. Likewise, the overview it provides enables the comparison between the analyzed units and their organization into a hierarchy to observe their evolution (Joint Research Centre, 2008).

CIs have been applied to different areas to assess corporate social responsibility (Dočekalová and Kocmanová, 2016; Staessens et al., 2019; Aparicio et al., 2020), measure the sustainability or competitiveness of tourism (Gómez-Vega and Picazo-Tadeo, 2019; Lozano-Oyola et al., 2019; Cabello et al., 2020), and evaluate the management of public administration services (Lo Storto, 2016; D'Inverno et al., 2018; D'Inverno and De Witte, 2020), public health (Martín-Martínez et al., 2019; Fu et al., 2020; Murtas et al., 2020), and education (Murias et al., 2008; El Gibari et al., 2018).

In the water sector, there are specific water CIs such as the Water Poverty Index (Sullivan, 2002; Sullivan et al., 2006), the Canadian Water Sustainability Index (Policy Research Initiative, 2007), the Watershed Sustainability Index (Chaves and Alipaz, 2007), and the West Java Water Sustainability Index (Juwana et al., 2010). There are also CIs that evaluate the performance of water companies under each dimension (social, environmental, and economic) of sustainability (Pérez et al., 2019). CIs have also been used to evaluate the sustainability of activities related to wastewater treatment (Molinos-Senante et al., 2014; Sabia et al., 2016; Sun et al., 2020). However, the article by Kumasi and Agbemor (2018) seems to be the only one to have focused on user satisfaction with a water service.

Thus, CIs are common in research on services and the water sector, but they have never been applied specifically to analyze users' perceptions of water supply quality. This study covers this research gap by focusing on whether (and how) it is possible to construct a CI index to approximate domestic water users' perceptions of quality. To do so, this paper offers a new application of a CI, using MCDA with common weights from DEA, to calculate a proxy of water supply service quality based on the variables that are considered to affect quality as perceived by users. The motivation is to help managers in the water distribution sector improve the quality of the water supply service (at the municipal level) by incorporating user perception variables quickly, simply, and objectively. This approach is justified by the fact that understanding consumers' perceptions of tap water is an important issue for water authorities and utility managers (Proulx et al., 2010). This method is also expected to identify the variables that exert the greatest impact on users to improve water supply management.

Furthermore, this study is also novel in that it combines economic, technical, and service quality variables, as perceived by users, into a single indicator for water managers. Technical and economic sustainability is thus combined with social aspects to provide highly useful information for managers and public officials. In addition, the CI is compatible with other methods (such as surveys) and offers an alternative to analyze users' opinions and take these opinions into account in water supply management. Such insight can help improve water supply so that the service provided is met with the greatest possible acceptance by users.

The CI was applied to a sample of 32 of the 45 municipalities in the metropolitan area of the city of Valencia (Spain). Six facets of water supply quality that are relevant to users (network quality, water quality, water price, complaints, inconvenience caused by upgrading the network, and continuity of service) were aggregated in a CI. All data were provided by Global Omnium, the water distribution company in these municipalities. Thus, this study is based on primary data sources, highlighting the approach that should be followed in future applications carried out by companies in the sector.

The results of the proposed model applied to these municipalities are expected to reflect the quality levels of the water supply service. The model aims to identify the main factors (inconvenience caused by upgrading the network, the efficiency of the network due to its effects on the taste of water, and the price of water) to help managers improve the service they provide. In the case study, the results show a high level of quality performance of the water supply service.

This article is structured as follows. Section 2 reviews the literature on CI, DEA, and MCDA methods and the areas where they have been used. Section 3 describes the model applied in this study to achieve the research objectives. Section 4 presents the variables and the data. Section 5 provides the results of the empirical analysis. Finally, Section 6 presents the conclusions and future research lines.

2. Literature review

2.1. Composite indicators, DEA, and MCDA in water management

Composite indicators are built by aggregating a group of variables into a single parameter to measure concepts that cannot be defined any other way. A CI is based on a theoretical framework, which is used to select, combine, and weight variables that reflect the dimensions or structure of the phenomenon or phenomena being measured (Joint Research Centre, 2008).

Numerous methods can be used to create a CI, provided that the OECD standards (Joint Research Centre, 2008) are met. These methods include the analytic hierarchy process (Molinos-Senante et al., 2014; Sun et al., 2020), TOPSIS (Fu et al., 2020), multi-criteria analysis (El Gibari et al., 2018; Mao et al., 2019; Pérez et al., 2019; Cabello et al., 2020), and methods derived from any of these approaches, such as MRP-WSCI, which is based on multi-criteria analysis (Ruiz et al., 2020) and data envelopment analysis (DEA). More specifically, DEA has been used to create CIs for evaluation in different sectors: services in airports (Baltazar et al., 2014), suppliers' green performance (Dobos and Vörösmarty, 2014), tourism (Gómez-Vega and Picazo-Tadeo, 2019), and corporate social responsibility (Staessens et al., 2019; Aparicio et al., 2020).

The proposed CI in this study was designed using MCDA, with weights based on DEA. Both MCDA and DEA are used in water economics and water resources management. DEA is a linear programming tool for evaluating the performance of a set of peer entities that use one or more inputs to produce one or more outputs. It has been widely used in water resources management, specifically in urban water supply. This methodology has been used in studies of efficiency/inefficiency (Al-Assa'd and Sauer, 2010; Romano and Guerrini, 2011; Kulshrestha and Vishwakarma, 2013; Ananda, 2014; Molinos-Senante et al., 2018; Ablanedo-Rosas et al., 2020), eco-efficiency/sustainable efficiency (Molinos-Senante et al., 2016a; Gémar et al., 2018; Lombardi et al., 2019; Delgado-Antequera et al., 2021), sector regulation efficiency (Cabrera Jr et al., 2018), service ownership (García-Sánchez, 2006; Munisamy, 2009; Lo Storto, 2013; Suárez-Varela et al., 2017), the effects of (structural) sector reforms on efficiency and productivity (Abbott et al., 2012; Ferreira da Cruz et al., 2012), growth of the efficiency/-productivity of utilities in water supply (Nyathikala and Kulshrestha, 2017), and the quality of the service provided to customers in terms of efficiency (Woodbury and Dollery, 2004; Kumar and Managi, 2010; Molinos-Senante et al., 2016c; Maziotis et al., 2017). MCDA has been used in water resources management (Calizaya et al., 2010; Amorocho-Daza et al., 2019; Bera and Banik, 2019; Psomas et al., 2021) and in the management of urban water supply (Lai et al., 2008; Carriço et al., 2012; Cordão et al., 2020; Cunha et al., 2020). For details on the use of MCDA in sustainability, see Goyal et al. (2020).

DEA and MCDA have similarities, principally in terms of the mathematical structure and methods for solution (Belton and Stewart, 1999). There is scant literature comparing these two methodologies for measuring efficiency. In the MCDA versus DEA literature, Baltazar et al. (2014) reported that the MCDA approach seems to be very promising when compared with traditional DEA-based approaches. Among the advantages of using DEA to construct CIs, the following should be noted: it provides a measure of performance based on real data; DEA models do not require the normalization of the initial data; DEA respects the individual characteristics of the units and their own particular value systems (Hatefi and Torabi, 2010; 2018); and the index constructed using DEA techniques has major advantages in terms of weighting and aggregating the partial indicators (Reig, 2015).

DEA has been considered appropriate for monitoring and control because it seeks to extract as much as possible from objective, historical data, without resorting to subjectivity, whereas MCDA is most appropriate for evaluation and choice because it seeks to elicit, understand, and manage value judgments. However, there are many applications in the field of DEA, with increasing attention on the desirability of incorporating value judgments in some analyses. In this sense, the two approaches are complementary (Belton and Stewart, 1999). In fact, in the literature, the DEA-MCDA model is a commonly used method that has been applied for a variety of purposes, such as to construct the Human Development Index (Hatefi and Torabi, 2010) and the Sustainable Energy Index (Hatefi and Torabi, 2010; Wang, 2015), to minimize total costs in assembly lines (Zahiri et al., 2016), to evaluate the efficiency of airports (Jardim et al., 2015), and to manage hazardous waste (Ali et al., 2015). In the water sector, the MCDA-DEA approach has been applied to evaluate the sustainability of water companies (Pérez et al., 2019). Finally, a notable study using MCDA and DEA together is the study by Reig (2015), who built a CI of quality of life to compare the quality of urban life in 43 cities belonging to the Metropolitan Area of Valencia (the same geographical area as in this study). The findings provide a complete ranking of all the cities in the sample.

This use of the DEA-MCDA model enables the construction of CIs from among all DMUs (decision-making units) via a set of common weights. The model is capable of discriminating DMUs that receive a CI score of 1 (i.e., the efficient entities leading to the determination of a single optimal DMU). The common weights structure of the proposed model has more discriminatory power than those obtained by previous DEA-like models (Hatefi and Torabi, 2010). In order to overcome the limitations of the model, new proposals have been developed (Sanei et al., 2011; Darehmiraki and Behdani, 2013; Hatefi and Torabi, 2018).

2.2. Determinants of water supply service quality

In order to create a CI, the objective selection of the variables that directly affect the quality of the service and users' perceptions of the quality of the service is essential. With DEA, it is not possible to test the significance of the variables. Therefore, the variables that have previously been used in the literature must be identified to ensure appropriate variable selection.

Network quality is related to network efficiency, defined as the difference between the water input and the water output in the water distribution network. Water leaks not only result in expensive maintenance but can also cause considerable environmental impact and social discontent when the water demand is not properly satisfied (Zhang et al., 2019). In the case of users, the inefficiency of the network is perceived as the entry of foreign substances into the drinking water, their effect on organoleptic properties (smell and taste), and their impact on public health (Molinos-Senante et al., 2016c; Cabrera et al., 2017; Wijesiri et al., 2018).

In addition to the year of installation and proportion of water leakage, the type of pipe materials is an important determinant of water quality. Even if water treatment plants produce high-quality water, the pipe network quality provides additional assurance of drinking water quality. In this sense, the effect of distribution network materials on water quality at the consumer's end (Sadiq et al., 1997) should be considered. However, the fact that some poisoning and water-borne diseases result from the low quality of the water pipe network should not be disregarded (Solgi et al., 2016). The distribution infrastructure is typically buried underground, and it is often difficult to assess the condition of the system. In case of breakages in the underground pipe network, external agents such as microorganisms may enter the distribution system and react with the residual disinfectant (chlorine), which results in faster decay (Mortula et al., 2019). Maintaining a hygienic water distribution infrastructure is crucial to provide high-quality services to consumers.

Water quality is observable by the municipality and the operator. It is an important parameter when assessing the quality of the water supply. Together with network quality, it is one of the most widely studied parameters (Khadse et al., 2011, 2016; García-Ávila et al., 2018; Asghari et al., 2019). There are studies of the relationship between the presence of microorganisms and turbidity (LeChevallier et al., 1981; Mccoy and Olson, 1986; Gauthier et al., 2003; Huey and Meyer, 2010). Other studies refer to the subproducts derived from water disinfection and their impact on health (Matia-Ribot, 1997; Bertelli et al., 2018; Wang et al., 2019). Finally, numerous articles link water quality to the implementation of water safety plans, a new management methodology of the World Health Organization based on risk analysis (Davison et al., 2005; Gunnarsdottir et al., 2012a, 2012b; Li et al., 2020).

As regards water quality, perceptions of tap water are subject to a wide range of factors and interactions including organoleptic perceptions, microbiological and chemical quality, prior experiences, information sources, trust in water companies and other groups, and perceived control and contextual factors (Delpla et al., 2020). Variables commonly used to determine users' perceptions of water quality are the taste and smell of water. The parameters taste and smell are used in surveys to study perceptions of the water service (Burlingame et al., 2017; Dietrich and Burlingame, 2020). There are also studies on the factors that affect perceptions of water, which are closely linked to water quality and the efficiency of the distribution network (Platikanov et al., 2017; Delpla et al., 2020; Romano and Masserini, 2020) or consumption preferences for tap water versus bottled water based on water quality and other preferences (Etale et al., 2018; Qian, 2018; Geerts et al., 2020). socioeconomic parameters influence user satisfaction and risk perception (Ellawala and Priyankara, 2016). Specifically, price has a major influence on users and offers an economic instrument to modify the demand for water, and therefore its consumption. In general, users are very sensitive to this variable because they demand greater or lesser consideration depending on what they pay (Hernández-Sancho et al., 2012; González-Gómez and García-Rubio, 2018; Marzano et al., 2018). An increasing amount of literature focuses on the effect of prices on users (García-Valiñas et al., 2010b; García-Valiñas and Picazo-Tadeo, 2015; González-Gómez and García-Rubio, 2018), as well as water tariffs (García-Rubio et al., 2015; Suárez-Varela et al., 2015; Lopez-Nicolas et al., 2018; Suárez-Varela and Martínez-Espiñeira, 2018; Fuente, 2019).

In the case of the city of Valencia, the elasticity of the domestic water demand at the average price is estimated at −0.88. That is, consumers in Valencia decrease their water consumption by 0.88% when the average price per m^3 increases by 1% in their bill from the previous period (Maldonado-Devis and Almenar-Llongo, 2021). This demand elasticity is higher than the estimated elasticity in studies of other Spanish cities (Martínez-Espiñeira, 2003; Arbúes et al., 2004; Martínez-Espiñeira and Nauges, 2004; Arbues and Villanua, 2006; García-Valiñas et al., 2010b).

Finally, the International Water Association (IWA) includes several variables with a major influence on water supply quality for users in the quality-of-service category, such as number of complaints and continuity of service (Alegre et al., 2016; Cabrera et al., 2017). For example, the inconvenience caused by network upgrades negatively affects users of the water supply service. Specifically, inconvenience to users caused by upgrades include traffic problems such as finding parking spaces and driving home (Molinos-Senante et al., 2016d; Cabrera et al., 2017). Therefore, complaints, continuity of service, and the inconvenience of upgrading the network are used in efficiency analysis to evaluate companies' service management (Molinos-Senante et al., 2016b; Molinos-Senante et al., 2016c; Maziotis et al., 2017).

3. Method

An MCDA model with common weights was used to calculate the CI. This model is based on DEA, as proposed by Hatefi and Torabi (2010). There are four main advantages to this model. First, it evaluates all decision-making units (DMUs) using the same set of weights, thus enabling fair comparison among them. Second, it provides a complete ranking of the analysis units to give a single unit with a CI of 1 (Hatefi and Torabi, 2010). Third, it requires only one step to calculate the results, which makes obtaining a solution with this model easier than with other models (Zhou et al., 2007). Fourth, it eliminates the requirement for any value judgments (subjectivity) to obtain the solution because the decision maker does not need to define the value of any parameters (Hatefi and Torabi, 2010).

With this model, it is assumed that there are m DMUs that use the same inputs to generate the same outputs. The goal is to obtain an aggregate measure that indicates their level of performance (Hatefi and Torabi, 2010). This aggregate measure is based on the values of the n subindicators, which may be given in different units of measurement. Therefore, they must be normalized with respect to their means. A better performance level of the DMU is associated with higher values of the subindicators.

The model is specified in Eq. (1), where $i = 1, \ldots, m$ represents each of the DMUs, $j = 1, \ldots, n$ represents each of the subindicators, I_{ij} represents each of the subindices, d_i is the deviation of the efficiency of the DMU_i, w_j is the weight given by the model for subindicators j, ε is an infinitesimal constant (generally 10^{-5}), and $M = \max\{d_i\}$.

$$\begin{aligned} & Min\ M \\ & \quad s.t. \\ & M - d_i \geq 0,\ i: 1, \ldots, m \\ & \sum_{j=1}^{n} w_j I_{ij} + d_i = 1, \quad i: 1, \ldots, m \\ & w_j \geq \varepsilon,\ d_i \geq 0,\ i: 1, \ldots, m,\ j: 1, \ldots, n \end{aligned} \tag{1}$$

With the resulting d_i^* of the optimization of the model in Eq. (1), the CIs would be calculated as $CI_i = 1 - d_i^*$.

However, the model considered in Eq. (1) may lead to the existence of several DMUs with $CI = 1$. To eliminate this multiplicity, obtain a single DMU with $CI = 1$, and provide a ranking, the model specified in Eq. (2) is applied.

$$\begin{aligned} & Min\ M - K \sum_{e\ \epsilon\ EF} d_e \\ & s.t. \\ & M - d_i \geq 0,\ i: 1, \ldots, m \\ & \sum_{j=1}^{n} w_j I_{ij} + d_i = 1, \quad i: 1, \ldots, m \\ & w_j \geq \varepsilon,\ d_i \geq 0,\ i: 1, \ldots, m,\ j: 1, \ldots, n \end{aligned} \tag{2}$$

In this model, EF represents the set of units with $CI = 1$, and K is a parameter ranging from 0 to 1. This model is solved starting with $K = 0.001$ and obtaining a solution by increasing the value of K by 0.001 until the number of DMUs with $CI = 1$ is 1. In some cases, the initial value of K must be reduced to achieve convergence (Hatefi and Torabi, 2010).

In addition, MCDA-DEA also provides the level at which each of the subindices of each DMU with $CI < 1$ could improve. The model proposed by Hatefi and Torabi (2018) is used, as shown in Eq. (3).

$$\begin{aligned} & Max \sum_{k=1}^{m} \mu_k - \sum_{k=1}^{m} \nu_k + \varepsilon \sum_{j=1}^{n} \tau_j \\ & s.t. \\ & \sum_{k=1}^{m} \mu_k \leq 1,\ k: 1, \ldots, m \\ & \sum_{j=1}^{n} (\mu_k + \nu_k) I_{kj} - \tau_j = I_{ij}, \quad j: 1, \ldots, n \\ & \mu_k \geq 0,\ \nu_k \geq 0,\ \tau_j \geq 0,\ k: 1, \ldots, m,\ j: 1, \ldots, n \end{aligned} \tag{3}$$

Here, μ_k, ν_k, τ_j are now the variables in the model in Eq. (3), and the resulting τ_j, as a solution, reflects the possible improvements of each of the subindices.

The phases of CI development are illustrated in a flowchart in Fig. 1.

4. Data and variables

The method to obtain CI, described in the previous section, was applied to the metropolitan area of the city of Valencia (Spain), with data from the year 2018. A sample of 32 of the 45 municipalities in the metropolitan area was used. The water services of these municipalities are managed by Global Omnium, a water company focused on the management of the entire water cycle. Each municipality in the study area was taken as a DMU. The selection of municipalities as DMUs is justified because the water supply system in each municipality is an independent unit with specific characteristics and a specific population in a defined territory.

Table 1 presents the key data. The municipalities in the study accounted for 73% of the total surface of the metropolitan area and 83% of the population. The sample included the municipality with the largest population in the metropolitan area (i.e., the city of Valencia).

The choice was constrained by the data provided by Global Omnium because at this stage of the research, data or indicators for other variables affecting water quality were unavailable. It is therefore a convenience sample. Nevertheless, the variables used in this study (see Table 2

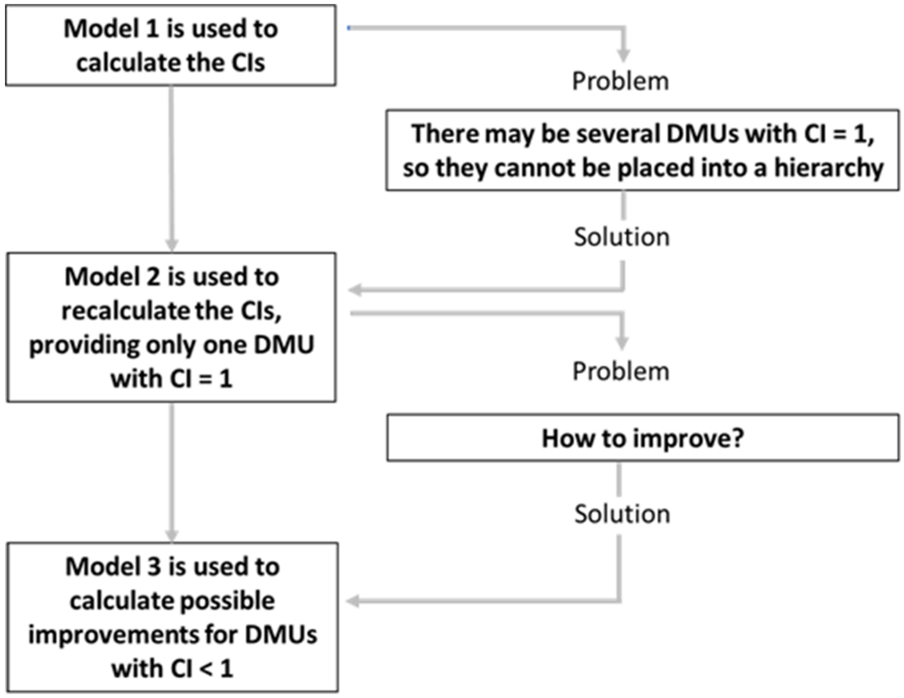

Fig. 1. Phases of CI development
Source: authors.

Table 1
Key data on the municipalities of the Valencia metropolitan area where the water supply was managed by Global Omnium in 2018.

Municipality	Population (number of inhabitants)	Area (km^2)	Muncipality	Population (number of inhabitants)	Area (km^2)
DMU_01	29,474	3.90	DMU_18	21,623	15.83
DMU_02	3900	4.62	DMU_19	6164	12.45
DMU_03	3911	4.42	DMU_20	25,241	3.93
DMU_04	9813	9.01	DMU_21	68,547	35.85
DMU_05	7308	2.74	DMU_22	20,658	85.79
DMU_06	14,495	0.78	DMU_23	7747	3.61
DMU_07	3629	1.05	DMU_24	19,531	18.06
DMU_08	37,575	3.44	DMU_25	8618	26.83
DMU_09	27,752	13.04	DMU_26	24,491	19.64
DMU_10	707	0.03	DMU_27	8870	4.20
DMU_11	7234	6.48	DMU_28	7004	2.34
DMU_12	13,031	8.40	DMU_29	10,179	1.83
DMU_13	30,630	19.65	DMU_30	9095	0.74
DMU_14	2462	2.53	DMU_31	787,808	134.63
DMU_15	15,553	6.16	DMU_32	3345	1.53
DMU_16	10,678	4.73	**Total study area**	**1290,115**	**460**
DMU_17	43,042	2.06	**Total metropolitan area**	**1559,084**	**628.81**

Source: Compiled by authors based on data from INE 2018.

Table 2
Variables used as subindicators.

Variable	Indicator
Network quality	Network efficiency (percentage)
Water quality	Percentage of water analyses that meet the quality level required by law
Water price	Euros per cubic meter
Complaints	Number of complaints per 1000 inhabitants
Inconvenience caused by upgrading the network	Number of actions per km of pipe
Continuity of service	Number of supply cuts per km of pipe

and Table 3) are representative of the standards of a good water supply service (according to the criteria of the International Water Association), are consistent with the reviewed literature, and represent the quality of the water supply service as perceived by users. It should be emphasized that the objective is to obtain a CI that replicates users' perceptions of the quality of the water supply service.

Although all data were sourced from Global Omnium, some variables were derived from the unprocessed data series, and other variables were constructed from Global Omnium's own data series. In particular, the data provided by Global Omnium included the number of users, network efficiency (percentage), network length (kilometers), total cubic meters billed, total number of water analyses, number of analyses not complying with the law, total amount billed in euros, number of claims per 1000 users, number of actions developed to improve the water distribution network, and number of network closures due to network improvement actions. Network efficiency (network quality) and number of complaints per 1000 users (complaints) were used without transformation.

Table 3
Mean and standard deviation of the indicators.

	Network efficiency (percentage)	Percentage of water analyses that meet the quality level required by law	Euros per cubic meter	Complaints number per 1000 inhabitants	Number of actions per km of pipe	Number of supply cuts per km of pipe
Mean	72.05	0.97	1.61	10.39	9.66	0.67
Standard deviation	15.70	0.06	0.31	10.38	4.89	0.94
Min.	25.90	0.70	0.99	1.67	4.56	0.05
Max.	89.83	1.00	2.24	50.11	27.83	5.37

Source: Authors based on data from Global Omnium Group.

The rest of the variables were obtained from the original series provided by Global Omnium: the water price variable was obtained by dividing the total amount invoiced in euros by the total cubic meters invoiced; the water quality variable was calculated as the ratio between the number of analyses that did not comply with the law and the total number of water analyses carried out; the variables inconvenience caused by upgrading the network and continuity of the service were obtained by dividing, respectively, the number of actions carried out to improve the distribution network and the number of network closures due to network improvement actions by the network length. The effect of the size of each municipality was thus eliminated to enable unitary comparison.

These variables can be classified into two categories: direct and indirect variables, both of which influence the dependent variable. Direct variables are measured in the same terms as the indicator, whereas indirect variables are measured in units other than those used for the indicator (Bustamante et al., 2021). Direct variables are defined as the closest variable in the chain of processes that link the variable to its impact (Mouton et al., 2013). Indirect variables indicate a quality gradient not well covered by the measured variables (i.e., they are probably proxies). In our case, the direct variables were most likely to affect users' service quality perceptions of network quality and water quality. The indirect variables were water price, complaints, inconvenience caused by network upgrades, and continuity of service.

The direct and indirect variables had a direct and inverse relationship with the quality of the water supply service. Regarding network quality and water quality, the higher the value of the selected indicator is, the better the quality of the water supply service (and therefore the perceptions of users) will be. Conversely, regarding water price, complaints, inconvenience caused by upgrading the network, and continuity of service, there is an inverse relationship with the variable quality of the water supply service (and therefore with users' perceived quality).

Finally, the existence of a relationship between the variables should be considered. For instance, network quality drives prices. Leakages are costly and can thus increase the water bill, but leakages are less costly than the investment needed for repairs to increase network quality (high levels of leakages can result in a cost trade-off between bearing the cost of losses and investing in the network to cut losses). In this case, incumbents can signal their quality by lowering prices (Porcher, 2011). In the sample used for this study, the Spearman correlation coefficient confirmed the non-existence of a correlation between the variables in each analyzed period.

5. Results

Table 4 shows the results of the water supply quality perceived by users in each of the 32 municipalities in 2018. The results are CIs obtained by applying the MCDA-DEA model to the six variables across the 32 municipalities in the sample. A value of 1 indicates the maximum quality that would be perceived by users. The assessment worsens as the CI moves away from the value 1. As the table shows, the mean value in the study area was 0.914 (with a standard deviation of 0.057). In total, 53% of the municipalities in the study area had an assessment that was above the average. The conclusion is that the water supply quality in the area of study is high.

Table 4
Water supply quality.

Municipality	Assessment	Municipality	Assessment
DMU_01	0.879	DMU_17	0.987
DMU_02	0.932	DMU_18	0.867
DMU_03	0.811	DMU_19	0.909
DMU_04	0.778	DMU_20	0.837
DMU_05	0.938	DMU_21	0.976
DMU_06	0.893	DMU_22	0.921
DMU_07	0.904	DMU_23	0.885
DMU_08	0.852	DMU_24	0.890
DMU_09	0.996	DMU_25	0.921
DMU_10	0.923	DMU_26	0.959
DMU_11	0.969	DMU_27	0.837
DMU_12	0.991	DMU_28	0.902
DMU_13	0.944	DMU_29	0.996
DMU_14	0.955	DMU_30	0.929
DMU_15	0.930	DMU_31	0.864
DMU_16	0.880	DMU_32	1.000

The model used to calculate the CI also indicates how much each variable must increase to improve the quality of the water supply management. The capacity to improve each variable to enhance the quality of the water supply service in each municipality was calculated for the 32 municipalities and the six variables in the sample. Table 5 shows the capacity for improvement of each variable.

To interpret the results in Table 5, it is necessary to differentiate between the direct and indirect variables. For the direct variables (network quality and water quality), the results indicate how much the value of these variables must increase to improve the water supply quality. By contrast, for the indirect variables (water price, complaints, inconvenience caused by upgrading the network, and continuity of service), the results indicate how much the value of the variable must decrease to improve the water supply quality. A value of 0 indicates that the variable is managed efficiently.

To illustrate this idea, DMU_01 can be taken as an example. Regarding the direct variables, to improve water supply quality, the values of two variables must increase: network quality by 9.51 and water quality by 1.69. In contrast, the values of the indirect variables should decrease: the value of complaints should decrease by 44.18, the inconvenience caused by upgrading the network should decrease by 7.24, and the continuity of the service should decrease by 0.39. In this case, the water price variable is already applied optimally and does not affect the service quality.

Another example is the DMU_31, which, due to the number of inhabitants, is easily identifiable as the city of Valencia. The most important variable with a direct relationship for users is water quality, which should increase by 6.99 to improve the perception of overall efficiency. The most important variable with an inverse relationship for users is the price of water, which should decrease by 35.43 to improve overall efficiency. Finally, the number of complaints is already applied optimally and does not have any effect on quality.

Table 5 also shows the mean values of the capacity for improvement of each variable. These values indicate which variables could improve

Table 5
Capacity for improvement of each variable.

Municipality	Direct variables Network quality	Water quality	Indirect variables Water price	Complaints	Inconvenience caused by upgrading the network	Service continuity
DMU_01	9.51	1.69	0.00	44.18	7.24	0.39
DMU_02	12.15	3.51	22.19	0.00	0.00	2.61
DMU_03	0.00	0.00	0.00	0.00	0.00	0.00
DMU_04	0.00	0.00	0.00	0.00	0.00	0.00
DMU_05	6.55	0.00	21.52	0.00	35.81	0.21
DMU_06	8.00	0.00	0.00	23.01	9.04	0.15
DMU_07	5.25	0.00	12.97	0.00	9.81	0.21
DMU_08	15.25	6.70	13.29	0.00	11.87	0.16
DMU_09	0.00	0.00	0.00	0.00	0.00	0.00
DMU_10	14.26	1.15	38.12	17.16	60.87	0.00
DMU_11	0.00	0.00	0.00	0.00	0.00	0.00
DMU_12	0.00	0.00	0.00	0.00	0.00	0.00
DMU_13	11.46	0.61	0.00	0.00	13.68	0.57
DMU_14	5.52	0.00	0.00	0.00	21.93	0.33
DMU_15	4.25	0.00	35.57	0.00	10.88	0.36
DMU_16	0.00	0.00	0.00	0.00	0.00	0.00
DMU_17	0.00	0.00	0.00	0.00	0.00	0.00
DMU_18	2.88	1.88	11.89	0.00	6.84	0.14
DMU_19	15.32	3.42	0.00	23.86	158.80	0.40
DMU_20	11.24	16.76	21.77	0.00	31.08	0.27
DMU_21	0.00	0.00	0.00	0.00	0.00	0.00
DMU_22	5.46	0.13	0.00	19.22	20.74	0.63
DMU_23	13.49	2.50	6.27	0.00	12.78	0.58
DMU_24	41.38	0.00	6.88	0.00	0.00	0.00
DMU_25	7.69	5.77	0.00	0.00	47.22	0.50
DMU_26	0.00	0.00	0.00	0.00	0.00	0.00
DMU_27	0.00	0.00	0.00	0.00	0.00	0.00
DMU_28	37.02	1.11	0.00	8.24	0.00	0.00
DMU_29	0.00	0.00	0.00	0.00	0.00	0.00
DMU_30	8.07	3.52	0.00	0.00	18.60	0.30
DMU_31	1.21	6.99	35.43	0.00	7.60	0.17
DMU_32	0.00	0.00	0.00	0.00	0.00	0.00
Mean	**7.37**	**1.74**	**7.06**	**4.24**	**15.15**	**0.25**
Standard deviation	**9.90**	**3.42**	**11.89**	**10.17**	**30.19**	**0.48**

the quality of the water supply service in the study area. Once the value of the capacity for improvement of each variable is known, the aspects that users perceive as most important can be ranked to help improve the management of the water supply.

The average values obtained in the previous table indicate the variables that users perceive as most important to improve the quality of the water supply. The capacity for improvement of the direct variables shows that the network quality variable has the greatest capacity for improvement and could therefore improve the overall quality of the water supply service the most. On the other hand, regarding the capacity enhancement of the indirect variables, the inconvenience caused by upgrading the network has plenty of room for improvement (following the established criteria of users' quality perceptions). The other variable with major capacity for improvement is water price.

6. Conclusions and discussion

The objective and main contribution of this article is the design of a CI to measure the quality of the water supply based on the variables that are considered to affect users' perceptions of the quality of water supply services in a simple, objective, and economical way. The MCDA model with common weights based on DEA was used for this purpose.

The proposed model meets all the methodological requirements established by the Joint Research centre-European Commission. Its main advantages are that it provides an overall indicator of users' perceptions and quantifies how much these indicators must change for these perceptions to improve. In addition, although approximating users' perceptions of the quality of water supply services is important, knowing which aspects have the most influence on this assessment can lead to a better, more efficient, and more socially accepted service. Accordingly, this methodology provides a new indicator to improve water supply management from a technical, economic, and social point of view, consistent with the notion of the circular economy.

The variables selected for this index are network quality (related to public health risk), water quality, water price, complaints, inconvenience caused by upgrading the network, and service continuity. These variables provide comprehensive information on the relevant aspects of users' quality of water supply services, combining technical, economic, and social variables.

Specifically, the proposed model was applied to a sample of 32 municipalities in the metropolitan area of Valencia (Spain). The results reflect an approximation of the quality-of-service provision, in an attempt to assess how users perceive the water service in the municipalities of the sample (however, the CI is not strictly speaking an indicator of users' perceptions). The average score was high, indicating a high degree of water supply quality. The model also shows how much each variable must be improved to enhance the quality of water supply management. In the case of these 32 municipalities, the factors for improvement are, in order, the inconvenience caused by upgrading the network, the efficiency of the network (linked to water taste), and price.

Nevertheless, the model has some limitations. These results offer theoretical quality perceptions of the service. Therefore, they should be compared with surveys to obtain a more realistic idea. From a methodological point of view, the weights of all variables are similar, even though their importance may differ. Despite the findings by Hatefi and Torabi (2010), the order of DMUs obtained in the second model (Eq. (2)) does not necessarily follow the hierarchy initially established in the first model (Eq. (1)) for the DMUs with $CI < 1$. In this respect, obtaining a single DMU with $CI = 1$ could establish a different hierarchy of the DMUs. Lastly, being a DEA approach, it also suffers from the limitations of that method. In particular, the model is deterministic, which implies that any inefficiency is due to the management procedure, with no room for randomness. Also, the DMUs involved in the analysis must use the same kind of inputs to generate the same kind of outputs.

However, none of these limitations critically affects the analysis presented in this study. The second one (i.e., the possibility of change in the hierarchy of the DMUs) is not necessarily a limitation, but a change due to a new imposed restriction that only one DMU can have $CI = 1$. The other limitations do not affect the procedure either because all the DMUs use the same type of inputs and produce the same kind of outputs, and the analysis aims to measure the quality of the water supply based on the variables that are considered to affect users' perceptions of quality (i.e., random effects are not included).

Regarding applicability, including users in decision making through the variables that affect their perceptions of the quality of the water supply service and having a quality index of water supply services can be extremely useful for management companies and local councils. Because the MCDA-DEA model shows the capacity for improvement of the factors included in the CI, this method indicates how to improve the quality considering the most common variables of perceived service quality. In this sense, the results obtained with this methodology can help managers improve their understanding of users' perceived quality of the water supply service in an objective, fast, simple, and economical way.

Finally,Finally, this study opens two possible future lines of research. The first one relates to comparing the results obtained by the CI with those of a survey of users to test the reliability of the model. The second one consists of determining the factors that influence users' evaluations of the variables used in this study. These suggestions will be addressed in future research to improve the proposed CI and thus provide more information on how to improve water supply services.

Authors statement

Palomero-González, José Antonio: Term, Conceptualization, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing.

Almenar-Llongo, Vicent: Term, Conceptualization, Writing - Review & Editing, Validation, Supervision.

Fuentes-Pascual, Ramón: Methodology

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2021.121300.

References

Ablanedo-Rosas, J.H., Guerrero Campanur, A., Olivares-Benitez, E., Sanchez-Garcia, J.Y., Nuñez-Ríos, J.E., 2020. Operational efficiency of Mexican water utilities: results of a double-bootstrap data envelopment analysis. Water, 12 (2), 553. https://doi.org/10.3390/w12020553.

Abbott, M., Cohen, B., Wang, W.C., 2012. The performance of the urban water and wastewater sectors in Australia. Util. Policy 20 (1), 52–63. https://doi.org/10.1016/j.jup.2011.11.003.

Al-Assa'd, T., Sauer, J., 2010. The performance of water utilities in Jordan. Water Sci. Technol. 62 (4), 803–808. https://doi.org/10.2166/wst.2010.907.

Alegre, H., Baptista, J.M., Cabrera Jr, E., Cubillo, F., Duarte, P., Hirner, W., Parena, R., 2016. Performance Indicators for Water Supply Services. IWA publishing. https://doi.org/10.2166/9781780406336.

Ali, M., Yadav, A., Anis, M., Sharma, P., 2015. Multiple criteria decision analysis using DEA-Topsis method for hazardous waste management: a case study of the USA. Int. J. Manag. Inf. Technol. 7 (3), 1–17. https://doi.org/10.5121/ijmit.2015.7301.

Amorocho-Daza, H., Cabrales, S., Santos, R., Saldarriaga, J., 2019. A new multi-Criteria decision analysis methodology for the selection of new water supply infrastructure. Water (Basel) 11 (4), 805. https://doi.org/10.3390/w11040805.

Aparicio, J., Kapelko, M., Monge, J.F, 2020. A well-defined composite indicator: an application to corporate social responsibility. J. Optim. Theory Appl. 186 (1), 299–323. https://doi.org/10.1007/s10957-020-01701-1.

Ananda, J., 2014. Evaluating the performance of urban water utilities: robust nonparametric approach. J. Water Resour. Plan. Manag. 140 (9), 04014021 https://doi.org/10.1061/(ASCE)WR.1943-5452.0000387.

Arbúes, F., Barberan, R., Villanua, I., 2004. Price impact on urban residential water demand: a dynamic panel data approach. Water Resour. Res. (11), 40. https://doi.org/10.1029/2004WR003092.

Arbues, F., Villanua, I., 2006. Potential for pricing policies in water resource management: estimation of urban residential water demand in Zaragoza, Spain. Urban Stud. 43 (13), 2421–2442. https://doi.org/10.1080/00420980601038255.

Arroyo-Menéndez, M., Sábada-Rodríguez, I., (Eds.). 2012. Metodología de la investigación social: técnicas innovadoras y sus aplicaciones. Síntesis. https://doi.org/10.3989/ris.2013.i2.

Asghari, F.B., Pakdel, M., Mohammadi, A.A., Yousefi, M., 2019. Spatial and temporal variation of physicochemical and microbial quality of drinking water for the distribution network in Maku. Iran. Desalin. Water Treat. 142, 82–89. https://doi.org/10.5004/dwt.2019.23365.

Aziz, J.A., 2005. Management of source and drinking-water quality in Pakistan. EMHJ-East. Mediterr. Health J. 11 (5–6), 1087–1098, 2005.

Baltazar, M.E., Jardim, J., Alves, P., Silva, J., 2014. Air transport performance and efficiency: MCDA vs. DEA approaches. Procedia Soc. Behav. Sci. 111, 790–799. https://doi.org/10.1016/j.sbspro.2014.01.113.

Belton, V., Stewart, T.J., 1999. DEA and MCDA: competing or complementary approaches? Advances in Decision Analysis. Springer, Dordrecht, pp. 87–104. https://doi.org/10.1017/CBO9780511611308.

Benito, B., Faura, Ú., Guillamón, M.D., Ríos, A.M., 2019. The efficiency of public services in small municipalities: the case of drinking water supply. Cities 93, 95–103. https://doi.org/10.1016/j.cities.2019.04.016.

Bera, K., Banik, P., 2019. Multi-criteria decision analysis (MCDA) for surface water management plan, a case study of Kansachara sub-watershed, West Bengal, India. Water Supply 19 (7), 2156–2162. https://doi.org/10.2166/ws.2019.096.

Bertelli, C., Courtois, S., Rosikiewicz, M., Piriou, P., Aeby, S., Robert, S., Greub, G., 2018. Reduced chlorine in drinking water distribution systems impacts bacterial biodiversity in biofilms. Front. Microbiol. 9, 2520. https://doi.org/10.3389/fmicb.2018.02520.

Burlingame, G.A., Doty, R.L., Dietrich, A.M., 2017. Humans as sensors to evaluate drinking water taste and odor: a review. J. - Am. Water Works Assoc. 109 (11), 13–24. https://doi.org/10.5942/jawwa.2017.109.0118.

Bustamante, A., Sebastia, L., Onaindia, E., 2021. On the representativeness of openstreetmap for the evaluation of country tourism competitiveness. ISPRS Int. J. Geo-Inf. 10 (5), 301. https://doi.org/10.3390/ijgi10050301.

Byrnes, J., Crase, L., Dollery, B., Villano, R., 2010. The relative economic efficiency of urban water utilities in regional New South Wales and Victoria. Resour. Energy Econ. 32 (3), 439–455. https://doi.org/10.1016/j.reseneeco.2009.08.001.

Cabello, J.M., Navarro-Jurado, E., Thiel-Ellul, D., Rodríguez-Díaz, B., Ruiz, F., 2020. Assessing environmental sustainability by the double reference point methodology: the case of the provinces of Andalusia (Spain). Int. J. Sustain. Dev. World Ecol. 28 (1), 4–17. https://doi.org/10.1080/13504509.2020.1778582.

Cabrera, E., Dane, P., Haskins, S., Theuretzbacher-Fritz, H., 2017. Benchmarking Para Servicios De agua: Guiando a los Prestadores De Servicios Hacia La Excelencia. Editorial Universitat Politècnica de València, Valencia (Spain). https://doi.org/10.2166/9788483638651.

Cabrera Jr,, E., Estruch-Juan, E., Molinos-Senante, M., 2018. Adequacy of DEA as a regulatory tool in the water sector. The impact of data uncertainty. Environ. Sci. Policy 85, 155–162. https://doi.org/10.1016/j.envsci.2018.03.028.

Calizaya, A., Meixner, O., Bengtsson, L., Berndtsson, R., 2010. Multi-criteria decision analysis (MCDA) for integrated water resources management (IWRM) in the Lake Poopo Basin. Bolivia. Water Resour. Manag. 24 (10), 2267–2289. https://doi.org/10.1007/s11269-009-9551-x.

Carriço, N., Covas, D.I.C., Almeida, M.C., Leitão, J.P., Alegre, H., 2012. Prioritization of rehabilitation interventions for urban water assets using multiple criteria decision-aid methods. Water Sci. Technol. 66 (5), 1007–1014. https://doi.org/10.2166/wst.2012.274.

Casas-Anguita, J., Repullo-Labrador, J., Donado-Campos, J., 2003. La encuesta como técnica de investigación. Elaboración de cuestionarios y tratamiento estadístico de los datos (I). Aten. Primaria 31 (8), 527–538. https://doi.org/10.1016/S0212-6567(03)70728-8.

Chaves, H.M., Alipaz, S., 2007. An integrated indicator based on basin hydrology, environment, life, and policy: the watershed sustainability index. Water Resour. Manag. 21 (5), 883–895. https://doi.org/10.1007/s11269-006-9107-2.

Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., 2006. Creating Composite Indicators with DEA Analysis: The Case of the Technology Achievement Index. Joint Research Centre. European Commission, Italy. https://doi.org/10.1057/palgrave.jors.2602445.

Cordão, M.J.D.S., Rufino, I.A.A., Alves, Barros Ramalho, P, Barros Filho, M, N.M., 2020. Water shortage risk mapping: a GIS-MCDA approach for a medium-sized city in the Brazilian semi-arid region. Urban Water J 17 (7), 642–655. https://doi.org/10.1080/1573062X.2020.1804596.

Cunha, M., Marques, J., Savić, D., 2020. A flexible approach for the reinforcement of water networks using multi-criteria decision analysis. Water Resour. Manag. 34 (14), 4469–4490. https://doi.org/10.1007/s11269-020-02655-9.

Darehmiraki, M., Behdani, Z., 2013. A new DEA approach to rank alternatives in MCDA. J. Data Envel. Anal. Decis. Sci. 2013, 1–7. https://doi.org/10.5899/2013/dea-00013.

Davison, A., Howard, G., Stevens, M., Callan, P., Fewtrell, L., Deere, D., World Health Organization., 2005. Water safety plans: managing drinking-water quality from catchment to consumer World Health Organization.

Delgado-Antequera, L., Gémar, G., Molinos-Senante, M., Gómez, T., Caballero, R., Sala-Garrido, R., 2021. Eco-efficiency assessment of municipal solid waste services: influence of exogenous variables. Waste Manag 130, 136–146. https://doi.org/10.1016/j.wasman.2021.05.022.

Delpla, I., Legay, C., Proulx, F., Rodriguez, M.J., 2020. Perception of tap water quality: assessment of the factors modifying the links between satisfaction and water consumption behavior. Sci. Total Environ. 722, 137786 https://doi.org/10.1016/j.scitotenv.2020.137786.

Dietrich, A.M., Burlingame, G.A, 2020. A review: the challenge, consensus, and confusion of describing odors and tastes in drinking water. Sci. Total Environ. 713, 135061 https://doi.org/10.1016/j.scitotenv.2019.135061.

D'Inverno, G., Carosi, L., Ravagli, L., 2018. Global public spending efficiency in Tuscan municipalities. Socio-Econ. Plan. Sci. 61, 102–113. https://doi.org/10.1016/j.seps.2017.01.006.

D'Inverno, G., De Witte, K., 2020. Service level provision in municipalities: a flexible directional distance composite indicator. Eur. J. Oper. Res. 286 (3), 1129–1141. https://doi.org/10.1016/j.ejor.2020.04.012.

Dobos, I., Vörösmarty, G., 2014. Green supplier selection and evaluation using DEA-type composite indicators. Int. J. Prod. Econ. 157, 273–278. https://doi.org/10.1016/j.ijpe.2014.09.026.

Dočekalová, M.P., Kocmanová, A., 2016. Composite indicator for measuring corporate sustainability. Ecol. Indic. 61, 612–623. https://doi.org/10.1016/j.ecolind.2015.10.012.

El Gibari, S., Gómez, T., Ruiz, F., 2018. Evaluating university performance using reference point based composite indicators. J. Informetr. 12 (4), 1235–1250. https://doi.org/10.1016/j.joi.2018.10.003.

Ellawala, K.C., Priyankara, D.P.M.P., 2016. Consumer satisfaction on quantity and quality of water supply: a study in Matara. Southern Sri Lanka. Water Pract. Technol. 11 (3), 678–689. https://doi.org/10.2166/wpt.2016.073.

Etale, A., Jobin, M., Siegrist, M., 2018. Tap versus bottled water consumption: the influence of social norms, affect and image on consumer choice. Appetite 121, 138–146. https://doi.org/10.1016/j.appet.2017.11.090.

Ferreira da Cruz, N., Marques, R.C., Romano, G., Guerrini, A., 2012. Measuring the efficiency of water utilities: a cross-national comparison between Portugal and Italy. Water Policy 14 (5), 841–853. https://doi.org/10.2166/wp.2012.103.

Flores-Baquero, Ó., Giné-Garriga, R., Pérez-Foguet, A., Jiménez-Fernández de Palencia, A., 2013. Metas e indicadores post 2015 en agua y saneamiento: una revisión desde un enfoque de derechos humanos. http://hdl.handle.net/2117/26971.

Fu, Y., Xiangtianrui, K., Luo, H., Yu, L., 2020. Constructing composite indicators with collective choice and interval-valued TOPSIS: the case of value measure. Soc. Indic. Res. 152 (1), 117–135. https://doi.org/10.1007/s11205-020-02422-8.

Fuente, D., 2019. The design and evaluation of water tariffs: a systematic review. Utilities Policy 61, 100975.. https://doi.org/10.1016/j.jup.2019.100975.

García-Ávila, F., Ramos-Fernández, L., Pauta, D., 2018. Evaluation of water quality and stability in the drinking water distribution network in the Azogues city, Ecuador. Data in brief. Quezada, D., 18, 111–123. https://doi.org/10.1016/j.dib.2018.03.007.

García-Rubio, M.A., Ruiz-Villaverde, A., González-Gómez, F., 2015. Urban water tariffs in Spain: what needs to be done? Water (Basel) 7 (4), 1456–1479. https://doi.org/10.3390/w7041456.

García-Sánchez, I.M., 2006. Efficiency measurement in Spanish local government: the case of municipal water services. Rev. Policy Res. 23 (2), 355–372. https://doi.org/10.1111/j.1541-1338.2006.00205.x.

García-Valiñas, M.Á., Martínez-Espiñeira, R., González-Gómez, F., 2010a. Measuring water affordability: a proposal for urban centres in developed countries. Int. J. Water Resour. Dev. 26 (3), 441–458. https://doi.org/10.1080/07900627.2010.491971.

García-Valiñas, M.A., Martínez-Espiñeira, R., González-Gómez, F., 2010b. Affordability of residential water tariffs: alternative measurement and explanatory factors in southern Spain. J. Environ. Manage. 91 (12), 2696–2706. https://doi.org/10.1016/j.jenvman.2010.07.029.

García-Valiñas, M.A., Picazo-Tadeo, A.J., 2015. Introduction to reforming water tariffs: experiences and reforms. Utilities Policy 34 (C), 34–35. https://doi.org/10.1016/j.jup.2015.02.004.

Gauthier, V., Barbeau, B., Tremblay, G., Millette, R., Bernier, A.M., 2003. Impact of raw water turbidity fluctuations on drinking water quality in a distribution system. Environ. Eng. Sci. 2 (4), 281–291. https://doi.org/10.1139/S03-026.

Geerts, R., Vandermoere, F., Van Winckel, T., Halet, D., Joos, P., Van Den Steen, K., Vlaeminck, S.E., 2020. Bottle or tap? Toward an integrated approach to water type consumption. Water Res 173, 115578. https://doi.org/10.1016/j.watres.2020.115578.

Gémar, G., Gómez, T., Molinos-Senante, M., Caballero, R., Sala-Garrido, R., 2018. Assessing changes in eco-productivity of wastewater treatment plants: the role of costs, pollutant removal efficiency, and greenhouse gas emissions. Environ. Impact Assess. Rev. 69, 24–31. https://doi.org/10.1016/j.eiar.2017.11.007.

Gómez-Vega, M., Picazo-Tadeo, A.J., 2019. Ranking world tourist destinations with a composite indicator of competitiveness: to weigh or not to weigh? Tour. Manag. 72, 281–291. https://doi.org/10.1016/j.tourman.2018.11.006.

González-Gómez, F., García-Rubio, M.A., 2018. Prices and ownership in the water urban supply: a critical review. Urban Water J 15 (3), 259–268. https://doi.org/10.1080/1573062X.2018.1436187.

Goyal, P., Kumar, D., Kumar, V., 2020. Application of multicriteria decision analysis (MCDA) in the area of sustainability: a literature review. Int. J. Anal. Hierarchy Process 12 (3) hppts://doi.org/10.13033/ijahp.v12i3.720.

Gunnarsdottir, M.J., Gardarsson, S.M., Bartram, J., 2012a. Icelandic experience with water safety plans. Water Sci. Technol. 65 (2), 277–288. https://doi.org/10.2166/wst.2012.801.

Gunnarsdottir, M.J., Gardarsson, S.M., Elliott, M., Sigmundsdottir, G., Bartram, J., 2012b. Benefits of water safety plans: microbiology, compliance, and public health. Environ. Sci. Technol. 46 (14), 7782–7789. https://doi.org/10.1021/es300372h.

Hatefi, S.M., Torabi, S.A., 2010. A common weight MCDA–DEA approach to construct composite indicators. Ecol. Econ. 70 (1), 114–120. https://doi.org/10.1016/j.ecolecon.2010.08.014.

Hatefi, S.M., Torabi, S.A., 2018. A slack analysis framework for improving composite indicators with applications to human development and sustainable energy indices. Econom. Rev. 37 (3), 247–259. https://doi.org/10.1080/07474938.2016.1140286.

Heller, L., 2015. The crisis in water supply: how different it can look through the lens of the human right to water? Cad Saude Publica 31, 447–449. https://doi.org/10.1590/0102-311XPE010315.

Hernández-Sancho, F., Molinos-Senante, M., Sala-Garrido, R., Del Saz-Salazar, S., 2012. Tariffs and efficient performance by water suppliers: an empirical approach. Water Policy 14 (5), 854–864. https://doi.org/10.2166/wp.2012.154.

Huey, G.M., Meyer, M.L., 2010. Turbidity as an indicator of water quality in diverse watersheds of the Upper Pecos River Basin. Water (Basel) 2 (2), 273–284. https://doi.org/10.3390/w2020273.

Hutton, G., 2012. Monitoring "Affordability" of water and sanitation services after 2015: review of global indicator options. A Paper Submitted to the UN Office of the High Commissioner for Human Rights, p. 20.

Jardim, J., Baltazar, M.E., Silva, J., Vaz, M., 2015. Airports' operational performance and efficiency evaluation based on multicriteria decision analysis (MCDA) and data envelopment analysis (DEA) tools. J. Spat. Organ. Dyn. 3 (4), 296–310.

Jerome, C., Pius, A., 2010. Evaluation of water quality index and its impact on the quality of life in an industrial area in Bangalore, South India. Am. J. Sci. Res. 1 (3), 595–603. https://doi.org/10.5251/AJSIR.2010.1.3.595.603.

Joint Research Centre-European Commission, 2008. Handbook on Constructing Composite indicators: Methodology and User Guide. OECD publishing. https://doi.org/10.1787/9789264043466-en.

Juwana, I., Perera, B.J.C., Muttil, N., 2010. A water sustainability index for West Java–Part 2: refining the conceptual framework using Delphi technique. Water Sci. Technol. 62 (7), 1641–1652. https://doi.org/10.2166/wst.2010.453.

Kaplan, O., Yildirim, N.C., Yildirim, N., Tayhan, N., 2011. Assessment of some heavy metals in drinking water samples of Tunceli. Turkey. E-J. Chem. 8 (1), 276–280. https://doi.org/10.1155/2011/370545.

Kayser, G.L., Moriarty, P., Fonseca, C., Bartram, J., 2013. Domestic water service delivery indicators and frameworks for monitoring, evaluation, policy and planning: a review. Res. Public Health 10 (10), 4812–4835. https://doi.org/10.3390/ijerph10104812.

Khadse, G.K., Kalita, M., Pimpalkar, S.N., Labhsetwar, P.K., 2011. Drinking water quality monitoring and surveillance for safe water supply in Gangtok. India. Environ. Monit. Assess. 178 (1), 401–414. https://doi.org/10.1007/s10661-010-1699-6.

Khadse, G.K., Patni, P.M., Talkhande, A.V., Labhasetwar, P.K, 2016. Change in drinking water quality from catchment to consumers: a case study. SSustain. Water Resour. Manag. 2 (4), 453–460. https://doi.org/10.1007/s10661-011-2344-8.

Kulshrestha, M., Vishwakarma, A., 2013. Efficiency evaluation of urban water supply services in an Indian state. Water policy 15 (1), 134–152. https://doi.org/10.2166/wp.2012.072.

Kumasi, T.C., Agbemor, B.D., 2018. Tracking user satisfaction of rural water services in northern Ghana. J. Water Sanit. Hyg. Dev. 8 (2), 307–318. https://doi.org/10.2166/washdev.2018.140.

Kvale, S., 2012. Las Entrevistas En Investigación Cualitativa (Vol. 2). Ediciones Morata, Madrid, Spain. ISBN: 978-8471126306.

Kumar, S., Managi, S., 2010. Service quality and performance measurement: evidence from the Indian water sector. Int. J. Water Resour. Dev. 26 (2), 173–191. https://doi.org/10.1080/07900621003655726.

Lai, E., Lundie, S., Ashbolt, N.J., 2008. Review of multi-criteria decision aid for integrated sustainability assessment of urban water systems. Urban Water J. 5 (4), 315–327. https://doi.org/10.1080/15730620802041038.

LeChevallier, M.W., Evans, T.M., Seidler, R.J., 1981. Effect of turbidity on chlorination efficiency and bacterial persistence in drinking water. Appl. Environ. Microbiol. 42 (1), 159–167. https://doi.org/10.1080/15730620802041038.

Li, H., Smith, C.D., Cohen, A., Wang, L., Li, Z., Zhang, X., Zhang, R., 2020. Implementation of water safety plans in China: 2004–2018. Int. J. Hyg. Environ. Health 223 (1), 106–115. https://doi.org/10.1016/j.ijheh.2019.10.001.

Lopez-Nicolas, A., Pulido-Velazquez, M., Rougé, C., Harou, J.J., Escriva-Bou, A., 2018. Design and assessment of an efficient and equitable dynamic urban water tariff. Application to the city of Valencia. Spain. Environ. Modell. Softw. 101, 137–145. https://doi.org/10.1016/j.envsoft.2017.12.018.

Lo Storto, C., 2013. Are public-private partnerships a source of greater efficiency in water supply? Results of a non-parametric performance analysis relating to the Italian industry. Water (Basel) 5 (4), 2058–2079. https://doi.org/10.3390/w5042058.

Lo Storto, C., 2016. The trade-off between cost efficiency and public service quality: a non-parametric frontier analysis of Italian major municipalities. Municipalities 51, 52–63. https://doi.org/10.1016/j.cities.2015.11.028.

Lombardi, G.V., Stefani, G., Paci, A., Becagli, C., Miliacca, M., Gastaldi, M., Almeida, C. M.V.B., 2019. The sustainability of the Italian water sector: an empirical analysis by DEA. J. Clean. Prod. 227, 1035–1043. https://doi.org/10.1016/j.jclepro.2019.04.283.

Lozano-Oyola, M., Contreras, I., Blancas, F.J., 2019. An operational non-compensatory composite indicator: measuring sustainable tourism in Andalusian urban destinations. Ecol. Econom. 159 (C), 1–10. https://doi.org/10.1016/j.ecolecon.2019.01.008.

McMahon, S.K., 2002. The development of quality of life indicators—a case study from the municipality of Bristol. UK. Ecol. Indic. 2 (1–2), 177–185. https://doi.org/10.1016/S1470-160X(02)00039-0.

Maldonado-Devis, M., Almenar-Llongo, V., 2021. A panel data estimation of domestic water demand with IRT tariff structure: the case of the municipality of Valencia (Spain). Sustain 13 (3), 1414. https://doi.org/10.3390/su13031414.

Mao, F., Zhao, X., Ma, P., Chi, S., Richards, K., Clark, J., Krause, S., 2019. Developing composite indicators for ecological water quality assessment based on network

interactions and expert judgment. Environ. Modell. Softw. 115, 51–62. https://doi.org/10.1016/j.envsoft.2019.01.011.
Martínez-Espiñeira, R., 2003. Estimating water demand under increasing-block tariffs using aggregate data and proportions of users per block. Environ. Resour. Econ. 26 (1), 5–23. https://doi.org/10.1023/A:1025693823235.
Martínez-Espiñeira, R., Nauges, C., 2004. Is all domestic water consumption sensitive to price control? Appl. Econ. 36 (15), 1697–1703. https://doi.org/10.1080/0003684042000218570.
Martínez-Medino, C., Galán-González, A., 2004. Técnicas e Instrumentos De Recogida y Análisis De Datos. Editorial UNED, Madrid, Spain.
Martín-Martínez, M., Andreu-Sanchez, J.L., Sanchez-Alonso, F., Corominas, H., Perez-Venegas, J.J., Roman-Ivorra, J.A., Vela-Casasempere, P., 2019. A composite indicator to assess the quality of care in the management of patients with rheumatoid arthritis in outpatient rheumatology clinics. Reumatol Clin 15 (3), 156–164. https://doi.org/10.1016/j.reuma.2017.06.017.
Marzano, R., Rouge, C., Garrone, P., Grilli, L., Harou, J.J., Pulido-Velazquez, M., 2018. Determinants of the price response to residential water tariffs: meta-analysis and beyond. Modell. Softw. 101, 236–248. https://doi.org/10.1016/j.envsoft.2017.12.017.
Matia-Ribot, L.M., 1997. Subproductos generados en la desinfección de las aguas potables: situación actual y orientaciones futuras. Tecnol. y Cienc. del Agua (170), 18–28.
Maziotis, A., Molinos-Senante, M., Sala-Garrido, R., 2017. Assessing the impact of quality of service on the productivity of water industry: a Malmquist-Luenberger approach for England and Wales. Water Resour. Manag. 31 (8), 2407–2427. https://doi.org/10.1007/s11269-016-1395-6.
Mccoy, W.F., Olson, B.H., 1986. Relationship among turbidity, particle counts and bacteriological quality within water distribution lines. Water Res 20 (8), 1023–1029. https://doi.org/10.1016/0043-1354(86)90045-X.
Meier, B.M., Kestenbaum, J.G., Kayser, G.L., Amjad, U.Q., Bartram, J., 2014. Examining the practice of developing human rights indicators to facilitate accountability for the human right to water and sanitation. J. Hum. Rights Pract. 6 (1), 159–181. https://doi.org/10.1093/jhuman/hut031.
Molinos-Senante, M., Gómez, T., Garrido-Baserba, M., Caballero, R., Sala-Garrido, R., 2014. Assessing the sustainability of small wastewater treatment systems: a composite indicator approach. Sci. Total Environ. 497, 607–617. https://doi.org/10.1016/j.scitotenv.2014.08.026.
Molinos-Senante, M., Gémar, G., Gómez, T., Caballero, R., Sala-Garrido, R., 2016a. Eco-efficiency assessment of wastewater treatment plants using a weighted Russell directional distance model. J. Clean. Prod. 137, 1066–1075. https://doi.org/10.1016/j.jclepro.2016.07.057 https://doi.org/.
Molinos-Senante, M., Marques, R.C., Perez, F., Gómez, T., Sala-Garrido, R., Caballero, R., 2016b. Assessing the sustainability of water companies: a synthetic indicator approach. Ecol. Indic. 61, 577–587. https://doi.org/10.1016/j.ecolind.2015.10.009.
Molinos-Senante, M., Maziotis, A., Mocholí-Arce, M., Sala-Garrido, R., 2016c. Accounting for service quality to customers in the efficiency of water companies: evidence from England and Wales. Water Policy 18 (2), 513–532. https://doi.org/10.2166/wp.2015.062.
Molinos-Senante, M., Mocholi-Arce, M., Sala-Garrido, R., 2016d. Efficiency assessment of water and sewerage companies: a disaggregated approach accounting for service quality. Water Resour. Manag. 30 (12), 4311–4328. https://doi.org/10.1007/s11269-016-1422-7.
Molinos-Senante, M., Donoso, G., Sala-Garrido, R., Villegas, A., 2018. Benchmarking the efficiency of the Chilean water and sewerage companies: a double-bootstrap approach. Environ. Sci. Pollut. Res. 25 (9), 8432–8440 https:/doi.org/10.1007/s11356-017-1149-x.
Mortula, M.M., Ali, T.A., Sadiq, R., Idris, A., Al Mulla, A., 2019. Impacts of water quality on the spatiotemporal susceptibility of water distribution systems. CLEAN–Soil, Air, Water, 47 (5), 1800247. https://doi.org/10.1002/clen.201800247.
Munisamy, S., 2009. Efficiency and ownership in water supply: evidence from Malaysia. Int. Rev. Bus. Res. Pap. 5 (6), 148–260.
Mouton, A., De Baets, B., Goethals, P., 2013. Data-driven fuzzy habitat models: impact of performance criteria and opportunities for ecohydraulics. Ecohydraulics: an Integrated Approach, 93–107. https://doi.org/10.1002/9781118526576.ch5.
Murias, P., de Miguel, J.C., Rodríguez, D., 2008. A composite indicator for university quality assessment: the case of Spanish higher education system. Soc. Indic. Res. 89 (1), 129–146. https://doi.org/10.1007/s11205-007-9226-z.
Murtas, R., Decarli, A., Greco, M.T., Andreano, A., Russo, A.G., 2020. Latent composite indicators for evaluating adherence to guidelines in patients with a colorectal cancer diagnosis. Medicine (Baltimore) (8), 99. https://doi.org/10.1097/MD.0000000000019277.
Myers, D., 1987. Community-relevant measurement of quality of life: a focus on local trends. Urban Aff. Q. 23 (1), 108–125. https://doi.org/10.1177/004208168702300107.
Nyathikala, S.A., Kulshrestha, M., 2017. Performance and productivity measurement of urban water supply services in India. Water Sci. Technol. Water Supply 17 (2), 407–421. https://doi.org/10.2166/ws.2016.106.
Ortiz-Gómez, A.S., Nuñez-Espinoza, J.F., Mejía-Castillo, W.G., 2019. The social perception of drinking water quality and management in the municipality of las vueltas. Chalatenango, El Salvador. Tecnol. y Cienc. del Agua 10 (3), 124–155. https://doi.org/10.24850/j-tyca-2019-03-06.
Papageorgiou, J.C., 1976. Quality of life indicators. Int. J. Environ. Sci. 9 (3), 177–186. https://doi.org/10.1080/00207237608737626.
Pérez, F., Delgado-Antequera, L., Gómez, T., 2019. A two-phase method to assess the sustainability of water companies. Energies 12 (13), 2638. https://doi.org/10.3390/en12132638.
Platikanov, S., Hernández, A., González, S., Cortina, J.L., Tauler, R., Devesa, R., 2017. Predicting consumer preferences for mineral composition of bottled and tap water. Talanta 162, 1–9. https://doi.org/10.1016/j.talanta.2016.09.057.
Policy Research Initiative., 2007. Canadian water sustainability index retrieved 5 July 2007. https://doi.org/ 10.1016/j.ecolind.2016.06.017.
Porcher, S., 2011. Public-private partnerships, network quality and the life cycle of contracts: the case of water industries in France. Gregor & Chaire EPPP 1–24.
Proulx, F., Rodriguez, M.J., Sérodes, J.B., Miranda, L.F., 2010. Factors influencing public perception and use of municipal drinking water. Water Sci. Technol. Water Supply 10 (3), 472–485. https://doi.org/10.2166/ws.2010.511.
Psomas, A., Vryzidis, I., Spyridakos, A., Mimikou, M., 2021. MCDA approach for agricultural water management in the context of water–energy–land–food nexus. Oper. Res. 21 (1), 689–723. https://doi.org/10.1007/s12351-018-0436-8.
Qian, N., 2018. Bottled water or tap water? A comparative study of drinking water choices on university campuses. Water (Basel) 10 (1), 59. https://doi.org/10.3390/w10010059.
Reig, E., 2015. Calidad De Vida En Las Ciudades Del Área Metropolitana De Valencia: Un Análisis Comparativo Con DEA y MCDA. Working Papers 1509. Department of Applied Economics II, Universidad de Valencia.
Romano, G., Guerrini, A., 2011. Measuring and comparing the efficiency of water utility companies: a data envelopment analysis approach. Util. Policy 19 (3), 202–209. https://doi.org/10.1016/j.jup.2011.05.005.
Romano, G., Masserini, L., 2020. Factors affecting customers' satisfaction with tap water quality: does privatisation matter in Italy? J. Clean. Prod. 258, 120593 https://doi.org/10.1016/j.jclepro.2020.120593.
Ruiz, F., El Gibari, S., Cabello, J.M., Gómez, T., 2020. MRP-WSCI: multiple reference point based weak and strong composite indicators. Omega (Westport) 95, 102060. https://doi.org/10.1016/j.omega.2019.04.003.
Sabia, G., De Gisi, S., Farina, R., 2016. Implementing a composite indicator approach for prioritizing activated sludge-based wastewater treatment plants at large spatial scale. Ecol. Indic. 71, 1–18. https://doi.org/10.1016/j.ecolind.2016.06.053.
Sadiq, M., Zaidi, T.H., Muhanna, Al, H, Mian, A, A., 1997. Effect of distribution network pipe material on drinking water quality. J. Environ. Sci. Health - Toxic/Hazard 32 (2), 445–454. https://doi.org/10.1080/10934529709376553.
Salman, S.M., 2014. The human right to water and sanitation: is the obligation deliverable? Water Int. 39 (7), 969–982. https://doi.org/10.1080/02508060.2015.986616.
Sanei, M., Khoshtinat, F.Z., Khodadadi, M., 2011. An improved common weight MCDA-DEA approach to construct composite indicators. Aust. J. Basic Appl. Sci. 5 (12), 1471–1475.
Solgi, M., Bozorg-Haddad, O., Seifollahi-Aghmiuni, S., Ghasemi-Abiazani, P., Loáiciga, H. A., 2016. Optimal operation of water distribution networks under water shortage considering water quality. J. Pipeline Syst. Eng. 7 (3), 04016005 https://doi.org/10.1061/(ASCE)PS.1949-1204.0000233.
Staessens, M., Kerstens, P.J., Bruneel, J., Cherchye, L., 2019. Data envelopment analysis and social enterprises: analysing performance, strategic orientation and mission drift. J. Bus. Ethics 159 (2), 325–341. https://doi.org/10.1007/s10551-018-4046-4.
Suárez-Varela, M., Martinez-Espineira, R., González-Gómez, F., 2015. An analysis of the price escalation of non-linear water tariffs for domestic uses in Spain. Utilities Policy 34, 82–93. https://doi.org/10.1016/j.jup.2015.01.005.
Suárez-Varela, M., García-Valiñas, M., González-Gómez, F., Picazo-Tadeo, A.J., 2017. Ownership and performance in water services revisited: does private management really outperform public? Water Resour. Manag. 31 (8), 2355–2373. https://doi.org/10.1007/s11269-016-1495-3.
Suárez-Varela, M., Martínez-Espiñeira, R., 2018. A proposal for the analysis of price escalation within water tariffs: the impact of the water framework directive in Spain. Environ. Plan C Politics Space 36 (4), 726–749. https://doi.org/10.1177/2399654417719558.
Sullivan, C., 2002. Calculating a water poverty index. World Dev. 30 (7), 1195–1210. https://doi.org/10.1016/S0305-750X(02)00035-9.
Sullivan, C., Meigh, J., Lawrence, P., 2006. Application of the water poverty index at different scales: a cautionary tale. Water Int. 31 (3), 412–426. https://doi.org/10.1080/02508060608691942.
Sun, Y., Garrido-Baserba, M., Molinos-Senante, M., Donikian, N.A., Poch, M., Rosso, D., 2020. A composite indicator approach to assess the sustainability and resilience of wastewater management alternatives. Sci. Total Environ. 725, 138286 https://doi.org/10.1016/j.scitotenv.2020.138286.
United Nations General Assembly., 2010. The human right to water and sanitation.
Wang, H., 2015. A generalized MCDA–DEA (multi-criteria decision analysis data envelopment analysis) approach to construct slacks-based composite indicator. Energy 80, 114–122. https://doi.org/10.1016/j.energy.2014.11.051.
Wang, Y.H., Wu, Y.H., Du, Y., Li, Q., Cong, Y., Huo, Z.Y., Hu, H.Y., 2019. Quantifying chlorine-reactive substances to establish a chlorine decay model of reclaimed water using chemical chlorine demands. Chem. Eng. J. 356, 791–798. https://doi.org/10.1016/j.cej.2018.09.091.
Weisner, M.L., Root, T.L., Harris, M.S., Mitsova, D., Liu, W., 2020. The complexities of trust between urban water utilities and the public. Sustain. Water Resour. Manag. 6, 1–12. https://doi.org/10.1007/s40899-020-00407-6.
Wijesiri, B., Deilami, K., Goonetilleke, A., 2018. Evaluating the relationship between temporal changes in land use and resulting water quality. Environ. Pollut. 234, 480–486. https://doi.org/10.1016/j.envpol.2017.11.096.
Woodbury, K., Dollery, B., 2004. Efficiency measurement in Australian local government: the case of New South Wales municipal water services. Rev. Policy Res. 21 (5), 615–636. https://doi.org/10.1111/j.1541-1338.2004.00098.x.

Zahiri, B., Tavakkoli-Moghaddam, R., Rezaei-Malek, M., 2016. An MCDA-DEA approach for mixed-model assembly line balancing problem under uncertainty. J. Intell. Fuzzy Syst. 30 (5), 2737–2748. https://doi.org/10.3233/IFS-152027.

Zhang, K., Yan, H., Zeng, H., Xin, K., Tao, T., 2019. A practical multi-objective optimization sectorization method for water distribution network. Sci. Total Environ. 656, 1401–1412. https://doi.org/10.1016/j.scitotenv.2018.11.273.

Zhou, P., Ang, B.W., Poh, K.L., 2007. A mathematical programming approach to constructing composite indicators. Ecol. Econom. 62 (2), 291–297. https://doi.org/10.1016/j.ecolecon.2006.12.020.

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