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A new methodology for assessing water quality, based on data envelopment analysis: Application to Algerian dams

Ahmed Amin Soltani[a], Amar Oukil[b,*], Hamouda Boutaghane[c], Abdelmalek Bermad[d], Mohamed-Rachid Boulassel[e]

[a] VESDD Laboratory, Hydraulic Department, University of M'sila, P.O. Box 166 Ichebilia, 28000 M'sila, Algeria
[b] Department of Operations Management & Business Statistics, College of Economics & Political Science, Sultan Qaboos University, P.O. Box 20, Al Khoud PC 123, Oman
[c] Hydraulics Department, Engineering Faculty, Badji Mokhtar University, P.O. Box 12, Annaba, Algeria
[d] Hydraulics Department, Ecole Nationale Polytechnique d'Alger, P.O. Box 16182, Algiers, Algeria
[e] Department of Allied Health Sciences, College of Medicine & Health Sciences, Sultan Qaboos University, P.O. Box 20, Al Khoud PC 123, Oman

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ABSTRACT

The present paper aims to develop a new Water Quality Index (WQI) based on Data Envelopment Analysis (DEA). Rather than using subjective weights of a judgmental process as inputs of the DEA model, we propose more objective variables, identified as "optimistic closeness values", appropriately derived from the observed values of the hydrochemical parameters.

The proposed approach was employed to assess the water quality of 47 dams in Algeria, defined with a dataset of 10 hydrochemical parameters. The results of the DEA-based WQI application revealed that (i) 21.27%, 27.66%, 25.53%, 4.25% and 21.27% of the total dams are categorized as "Poor", "Marginal", "Medium", "Good" and "Excellent" water quality, respectively; (ii) the best water quality is found in "Kissir" and the worst one in "Bougara"; (iii) a priority scale on the hydrochemical parameters can be set for the treatment of water using the notion of slack value.

Collectively, the new methodology has proven its effectiveness not only for categorizing or ranking sites based on water quality but also as an alternative tool to be used to assist decision-makers in allocating funds and managing water resources.

1. Introduction

Water quality has become a common research issue in the water resource management field due to the increased deterioration of surface and groundwater quality, as a result of pollution. Polluting agents may include natural processes such as climate change, which causes precipitation and weathering, sediment transport, as well as anthropogenic activities, like domestic wastewater discharge and industrial toxic effluents (Bouguerne et al., 2017).

Water-borne diseases and impaired ecosystems are only samples of the disastrous effects of contaminated water on public health and environmental safety (Bilgin, 2018). Hence, the evaluation of water quality turned into a vital issue for local authorities as well as worldwide institutions, like World Health Organization (WHO) and Food and Agriculture Organization (FAO). Thresholds, known as guidelines, have been set on selected parameters in order to assess the quality of water for drinking, irrigation and other purposes. Water quality was assessed by comparing a long list of measured parameters with threshold values (Hamlat et al., 2014). This technique can be effective in identifying the variables that contribute to the degradation of the water body, but it reflects only a minor view of the overall state of water quality. Water Quality Index (WQI) is one of the most powerful tools for summarizing all hydrochemical variables into a single value (Rachedi and Amarchi, 2015). In 1965, Horton (1965) proposed the first modern WQI, which

Abbreviations: AHP, Analytic Hierarchy Process; AHS, Algerois–Hodna–Sommam; ANBT, Agence Nationale des Barrages et Transferts; ANRH, Agence Nationale des Resources Hydrauliques; BCC, Banker, Charnes, and Cooper; CCME–WQI, Canadian Council Ministers of the Environments WQI; CCR, Charnes, Cooper, and Rhodes; CSM, Constantinois–Seybousse–Mellegue; CZ, Cheliff–Zahrez; DEA, Data Envelopment Analysis; DM, Decision–Maker; DMU, Decision Making Unit; EC, European Commission; FAO, Food and Agriculture Organization; LP, Linear Programming; MCDM, Multi-Criteria Decision Making; NSF-WQI, National Sanitation Foundation's WQI; OCC, Oranie-Chott-Chergui; WHO, World Health Organization; WQI, Water Quality Index; WQS, Water Quality Standards; WRI, Water Risk Index

* Corresponding author.
E-mail addresses: ahmedamin.soltani@univ-msila.dz (A.A. Soltani), aoukil@squ.edu.om (A. Oukil), hamouda.boutaghane@univ-annaba.dz (H. Boutaghane), abdelmalek.bermad@g.enp.edu.dz (A. Bermad), boulassel@squ.edu.om (M.-R. Boulassel).

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Nomenclature

pH	Power of Hydrogen (/)	NO_2^-	Nitrite (mg/L)
TS	Total Solid (mg/L)	NH_4^+	Ammonia (mg/L)
DO	Dissolved Oxygen (%)	PO_4^{3-}	Phosphate (mg/L)
NO_3^-	Nitrate (mg/L)	BOD	Biochemical Oxygen Demand (mg/L)
		COD	Chemical Oxygen Demand (mg/L)
		OM	Organic Matter (mg/L)

was structured around four main steps: (i) Parameter selection, (ii) Making sub-indices, (iii) Assignment of weights and (iv) Obtaining the final index through the aggregation of the sub-indices. In the wake of this methodology, many WQIs have been developed with particular specifications, e.g., US National Sanitation Foundation's Water Quality Index (NSF-WQI) and Canadian Council Ministers of the Environments WQI (CCME WQI). Because they are considered official WQIs in their own countries, these two indices are the most popular and serve as benchmarks for the new indices developed by scientists (Abbasi and Abbasi, 2012). However, conventional indices have revealed serious shortcomings, including a limited number of selection parameters, most of which do not take into account toxic substances (heavy metals), lack consideration of uncertainties, and subjective and deterministic formulations of the equation indices (Ocampo-Duque et al., 2006). In the last few decades, advanced statistical analysis and artificial intelligence approaches have played a key role in the development of robust indices that overcome previous drawbacks through natural language reasoning and successful approximation of the calculated index among complex merged variables.

The application of Multi-Criteria Decision-Making (MCDM) techniques to develop WQIs is rather recent. Carbajal-Hernández et al., (2013) proposed a new WQI based on Analytic Hierarchy Process (AHP) to analyze the ecosystem in shrimp farms. Sutadian et al., (2017) employed AHP to estimate the aggregation weights to use with the water quality parameters toward the computation of the WQI. Meanwhile, it is noteworthy that MCDM approaches, including AHP, rely primarily on the opinion of experts as *a priori* preference information required for producing parameters' weights, which confers subjectivity to the evaluation process (Oukil and Govindaluri, 2020). Data Envelopment Analysis (DEA) is one of the methods that prevent resorting to *a priori* elicited weights due to its objective data-driven nature (Al-Mezeini et al., 2020; Oukil et al., 2016)

The strength of DEA is proven for performance evaluation of Decision Making Units (DMUs) that employ multiple inputs (resources) to produce multiple outputs (products/ services) and, hence, enable explicit segregation of these DMUs into efficient and inefficient units (Oukil and Al-Zidi, 2018). In water resources management, DEA is applied for assessing water supply distribution networks (Alsharif et al., 2008), improving the irrigation performance (Zema et al., 2018), quantifying vulnerability of surface water environment (Xiang et al., 2016), and comparing lakes performance (Alsharif and Fouad, 2012). Nevertheless, applications relating to the field of water quality have so far been limited.

The pioneering DEA study for developing WQI is due to Kavurmaci and Üstün (2016). The DEA-based WQI is established via a two-stage hybrid process involving 51 water samples, described with 19 hydrochemical parameters, and collected from irrigation wells in Sereflikochisar basin, Turkey. In the first stage, these parameters are clustered into 4 groups of vulnerability factors, where the first group includes basic physicochemical parameters, while the second, the third and the last groups comprise, respectively, major ions, toxic substances and undesirable elements. Using the feedbacks of fifteen water quality experts, an AHP is carried out with 4 criteria (groups of vulnerability factors), 19 sub-criteria (hydrochemical parameters), and 51 alternatives (irrigation wells). In the second stage, the experts' judgments, expressed through the AHP weights assigned to each of the 4 criteria, are used as the inputs of a DEA model to produce the wells' efficiency scores, i.e., the wells' WQIs. A few more applications of the described approach can be found in the water management literature, namely (Kavurmaci, 2016; Kavurmaci and Apaydin, 2019; Kavurmacı and Karakuş, 2020). Nevertheless, there are striking aspects that may need to be further investigated to improve the latter DEA approach, such as:

(1) The WQIs are not necessarily unique for the same sample of water sources. Indeed, the inputs of the DEA model are the weights of an AHP, which are fundamentally outcomes of experts' subjective judgments, regardless of their degree of expertise. As such, the DEA results, including the WQIs, vary depending on "who are the experts".
(2) The nature of the inputs of the DEA model cannot help specialists to adequately prioritize the hydrochemical parameters over the water treatment process. Very often, such prioritization is necessary to cope with budget restrictions or other technical considerations.

In order to address the aforementioned gaps, we propose a methodology that employs as inputs of the DEA model more objective variables, appropriately derived from the observed values of the hydrochemical parameters, rather than subjective weights of a judgmental process. The new input variable, called "optimistic closeness value", enables the robustness of the WQIs to be enhanced and a priority scale on the hydrochemical parameters to be customized for the water treatment at each water source.

The proposed methodology was applied on a sample of 47 dams, defined with 10 physicochemical parameters, and located in the hydrographic basin areas of the Tellian region, Algeria.

Accordingly, the contribution of this paper to the DEA-based water management literature is four-fold.

(1) A new input variable is defined on the grounds of the observed values of the hydrochemical parameters to circumvent the need for experts' opinion.
(2) A unique WQI is produced for each water source by using a standard DEA model, enabling a more consistent water risk assessment.
(3) A risk ranking procedure is developed through a combination of the WQIs and the benchmarking powers of the efficient water sources. As a result, water management decision-makers can identify the most vulnerable sites per hydrographic region, and develop appropriate plans to prioritize future actions.
(4) A prioritization procedure is presented for water treatment based on slack analysis.

The remaining of the paper unfolds as follows. Section 2 is dedicated to a brief description of the study area, as well as the data collection. The new methodology is presented in Section 3 and it is applied to the specific Algerian context in Section 4 along a detailed discussion of the results. The last section concludes with a summary of the most salient results together with possible venues for future research.

2. Study area

Algeria is located in North Africa, with the largest area of the continent, 2.381.741 Km^2, bordered by the Mediterranean Sea to the north, Mali and Niger to the south, Tunisia and Libya to the east and Morocco, Western Sahara and Mauritania to the west. In Algeria, there are three types of climate: the mild Mediterranean climate of the northern coast, with a wet winter and hot summer, the semi-arid climate of the hills and mountains in the center, which is a little more continental and moderately rainy, dry in summer and cold frosty in winter with occasional snowfalls on topographic reliefs that are > 900 m, and, finally, the desert climate of the vast area occupied by the Sahara, characterized by an arid climatology with hot temperatures throughout the year.

The average annual rainfall in Algeria varies from one region to another. The precipitation rate ranges between 600 and 1000 mm in the coastal part, between 400 and 600 mm in the highlands, and it is < 100 mm in the Sahara (Nouad, 1997). However, due to climate change vulnerability, Algeria has experienced severe persistent drought and flooding in recent years (Schilling et al., 2020), with the average annual temperature increasing by 0.65 to 1.45C° and the level of rainfall decreasing 5 to 13% (Boudiaf et al., 2020; Touitou and Abul Quasem, 2018). As a result, the country suffers serious water scarcity and it is, worldwide, ranked fourteenth among the poorest countries in water resources (Drouiche et al., 2012). In the meantime, Algeria has recorded a high population growth rate (1.98%), where the total population is expected to reach 45 million inhabitants in 2020 (Drouiche et al., 2020). In other words, there is a dramatic imbalance between water availability and demand, in spite of 17 billion m^3 water reserve (10 billion m^3 surface water and 7 billion m^3 groundwater) (Drought management strategy in Algeria, 2014). To cover the perceived deficit in water availability, the Algerian authorities have launched a new national strategy to explore non-conventional water sources such as seawater desalination and wastewater treatment, besides an ambitious program of building new dams and mobilizing water resources to areas affected by water shortages via large transfer projects and interconnected systems.

According to the National Agency of Dams and Transferts (*Agence Nationale des Barrages et Transferts*, ANBT), Algeria has currently 79 dams, operating with a capacity of about 8 billion m^3 However, the only data that was accessible pertains to the 47 large dams, as summarized in Table 1.

These dams are located in four hydrographic basin areas of the Tellian region, namely (i) Oranie–Chott–Chergui (OCC) (ii) Cheliff–Zahrez (CZ), (iii) Algerois–Hodna–Sommam (AHS) and (iv) Constantinois–Seybousse–Mellegue (CSM), as shown in Fig. 1.

The assessment of water quality in Algeria is carried out by the National Agency of Water Resources (*Agence Nationale des Resources Hydrauliques*, ANRH) through evaluating each hydrochemical parameter with respect to its standard. This process is often very laborious and time–consuming, especially with numerous parameters are measured. Furthermore, it does not give a comprehensive picture of the water quality status in the sampling area, hence, the pertinence of developing a local WQI.

To the best of our knowledge, research on using WQI for assessing dams' water quality in Algeria is still limited. The few extant studies have been conducted for individual reservoirs such as (Bouguerne et al., 2017; Bouslah et al., 2017) or specific regions (Hamlat et al., 2017, 2014), but none has been explicitly dedicated to the whole country.

The present study is therefore extremely important because it offers to ANRH stakeholders a powerful DEA–based tool that allows to (i) create nationally an effective water quality benchmarking system by assigning a proper WQI to each dam; (ii) allocate funds to the water treatment plants in sites and regions that are most affected by polluting resources; (iii) use a new index to determine the spatial–temporal variations and trends in water quality for any kind of water body (groundwater or surface water).

3. Methodological framework

In order to devise the new WQI, we develop the DEA-based approach depicted in Fig. 2.

The new methodology starts with creating an input variable that is more suitable to the data of the current study prior to the application of a DEA model. The outcomes of the DEA model include WQIs, benchmark frequencies and slack values are used for setting the bounds of the quality ranges, ranking the dams and designing a priority scale on the treatment of the hydrochemical parameters. A detailed description of the proposed methodology follows.

3.1. Water quality standards

Water quality standards (WQS) refer to satisfactory concentration values of the physicochemical and biological parameters that exist in a water sample. If the measured values of these parameters fall outside the specified water quality ranges, treatment must be carried out. World organizations, such as WHO, European Commission (EC) and others have established a series of laws and policies on WQS for different uses. For example, the consumption of drinking water containing nitrate (NO_3^-) at a level of 50 mg/L or more can lead to methemoglobinemia in infants WHO (2017). Therefore, the development of WQS is intended to protect public health and aquatic life from contaminations and diseases. In this study, we adopted the drinking WQS of the WHO (2017), the Union (2014) and the ANRH, (2009) to classify each hydrochemical parameter into four (04) categories of quality, namely Excellent, Acceptable, Poor and Unsuitable as shown in Table 2. The Excellent interval expresses the satisfactory quality of the water that can be used without any particular exigence, while the Acceptable, Poor and Unsuitable ranges require, respectively, simple, advanced and very advanced treatments to fulfill the desired water quality.

In what follows, we adopt the most optimistic stance, based on the Excellent range, to develop a new procedure for evaluating water quality level.

Note that the proposed procedure is developed exclusively on the grounds of the drinking WQS but it can be easily extended to irrigation WQS (Zahedi, 2017), as pointed in the next sections, wherever appropriate.

3.2. Defining new input variables

DEA is a non-parametric approach for evaluating the performance of DMUs relative to an efficiency frontier. Conventional DEA models include (CCR) Charnes, Cooper, and Rhodes (1978), and (BCC) Banker, Charnes, and Cooper (1984). For more on these models development, see, e.g., (Cooper et al., 2002)

The fundamental principle of conventional DEA consists of consuming fewer inputs to produce more outputs while evaluating a DMU's performance (Hassan and Oukil, 2020). Thus, each input, treated implicitly as a resource of a production process, does necessarily comply with the preference dictum *"less is better"* (Cook et al., 2014). In dealing with water quality parameters (refer to Table 3), the latter dictum does

Table 1
Characteristics of Algeria's large dams.

HydrographicBasin	Oranie Chott Chergui	Cheliff Zahres	Algerois Hodna Soummam	Constantinois Seybousse Mellegue	Total
Surface (Km^2)	76 000	56 200	50 000	43 000	225 200
Number of dams	9	16	10	12	47
Capacity (million m^3)	504	1 638	1 451	1 868	5 462

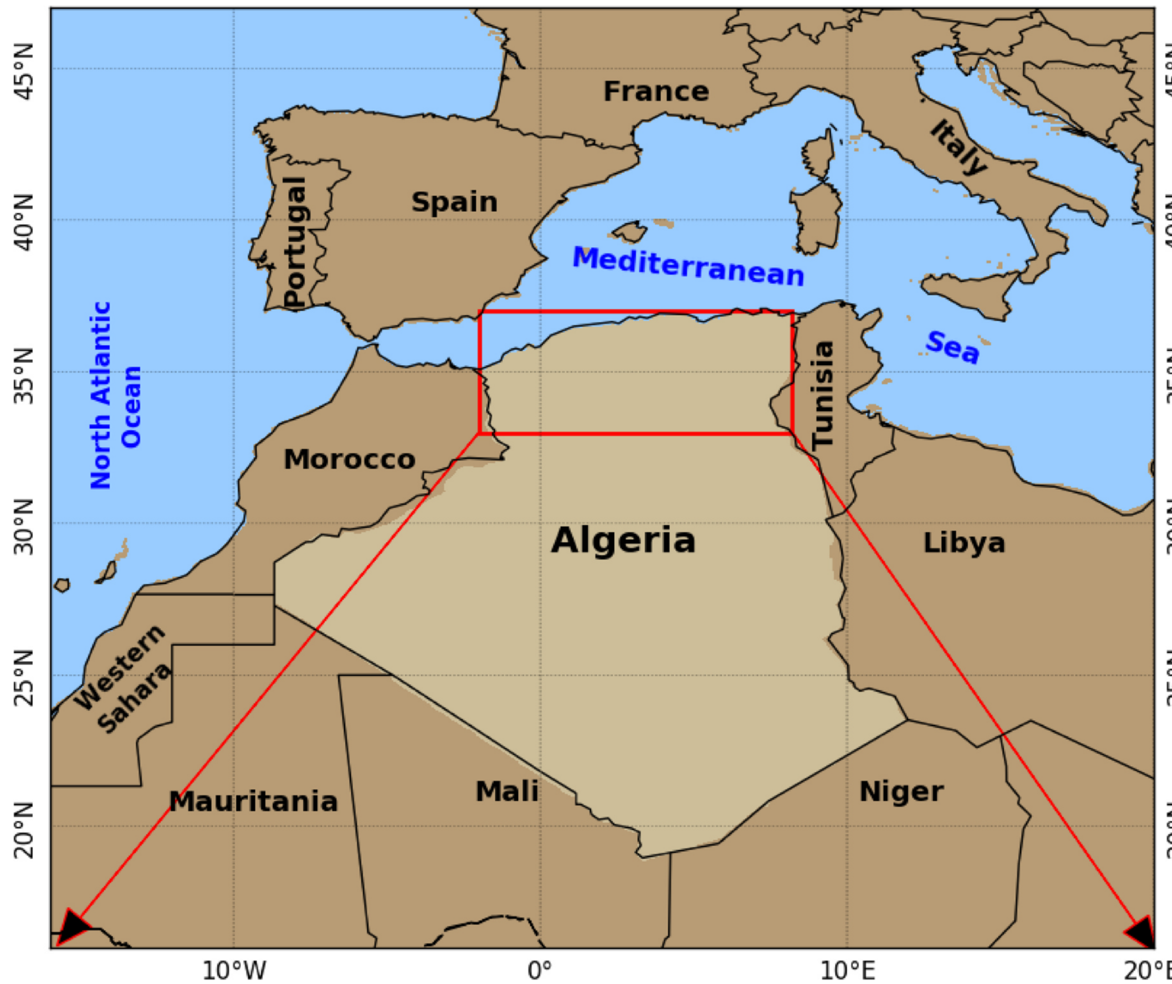

Fig. 1. Geographical locations of the sampling sites of water quality parameters.

not apply for Dissolved Oxygen (DO) and pH, although it accommodates well enough most of the other factors. In the case of DO, *"more is better"* appears more appropriate, whereas preferred pH values are bounded and, hence, do not conform to any of these dicta. Moreover, each factor is associated with separate clusters of values over the standard categorization of water quality as Unsuitable, Poor, Acceptable, and Excellent. Such a fragmentation of the preferential scale, together with the conflicting data settings among water quality parameters, renders a direct usage of their original values as inputs of a DEA model rather difficult.

Assume a set of K dams, each dam d defined with N water quality factors i using observed values x_{id}, for $i = 1, \ldots, N$. The standard categorization of water quality suggests that the ideal dam would have the values of all factors falling inside the "Excellent" range. Let $A_E = [a_i\ ,\ b_i]$ denote the set of preferred values for Excellent, i.e., if $x_{id} \in A_E$, water quality of dam d will be classified Excellent for factor i. Assuming that $x_{id} \notin A_E$, the closer x_{id} to one of A_E's bounds the better the quality of the water. An optimistic decision maker (DM) would support the viewpoint that each factor is potentially fit to reach its "Excellent" range.

To measure such potential, let s_{id} represent the optimistic closeness value, which is defined over three possible scenarios.

$$A_E = [a_i,\ +\infty[\text{ and } x_{id} < a_i \Rightarrow s_{id} = a_i - x_{id} + \varepsilon \tag{1}$$

$$A_E = [a_i,\ b_i] \text{ and } \begin{cases} x_{id} < a_i \Rightarrow s_{id} = a_i - x_{id} + \varepsilon \\ x_{id} > b_i \Rightarrow s_{id} = x_{id} - b_i + \varepsilon \end{cases} \tag{2}$$

$$A_E =]-\infty,\ b_i] \text{ and } x_{id} > b_i \Rightarrow s_{id} = x_{id} - b_i + \varepsilon \tag{3}$$

The term $\varepsilon > 0$ is an infinitesimal number that is meant to circumvent the occurrence of zero inputs and, hence, the potential infeasibility of the DEA linear programming (LP) model. Moreover, $s_{id} = \varepsilon$ is used to define the situation where $x_{id} \in A_E$.

Referring to the ranges of the water quality factors (Table 3), scenario (1) matches only DO, scenario (2) depicts pH case, and scenario (3) applies to all the remaining factors.

To better illustrate the meaning of the optimistic closeness value s_{id}, let us consider the quality factor pH, which is categorized as "Excellent" if its measured value $x_{id} \in [6.5,\ 8.5]$. Assume that the pH value of a water sample is $x_{id} = 9.01$, which clearly falls outside the "Excellent" range. Given that $x_{id} > 8.5$, it needs to be reduced with at least $s_{id} = 9.01 - 8.5 + \varepsilon = 0.51$ before pH can be declared as "Excellent".

Interestingly, irrespective of the water quality parameter, the variable s_{id} fulfills perfectly the preference dictum *"less is better"*. Therefore, each s_{id} can be regarded as input and each dam d will now be defined with N water quality factors i, using observed values x_{id}, for $i = 1, \ldots, N$. In the meantime, it is remarkable that large values of s_{id} do also reflect a high level of risk impact, which confers to the latter a possible role as risk indicator. Furthermore, the associated new water quality index, introduced in the next section, becomes a valid tool for rapid risk assessment (Kim et al., 2019; Nazeer et al., 2014).

3.3. Devising a new water quality index

In our study, a dam can be regarded as a DMU that employs, as inputs, the optimistic closeness values s_{id} of water quality factors, to produce a single output, which is, here, water (Kavurmaci and Üstün,

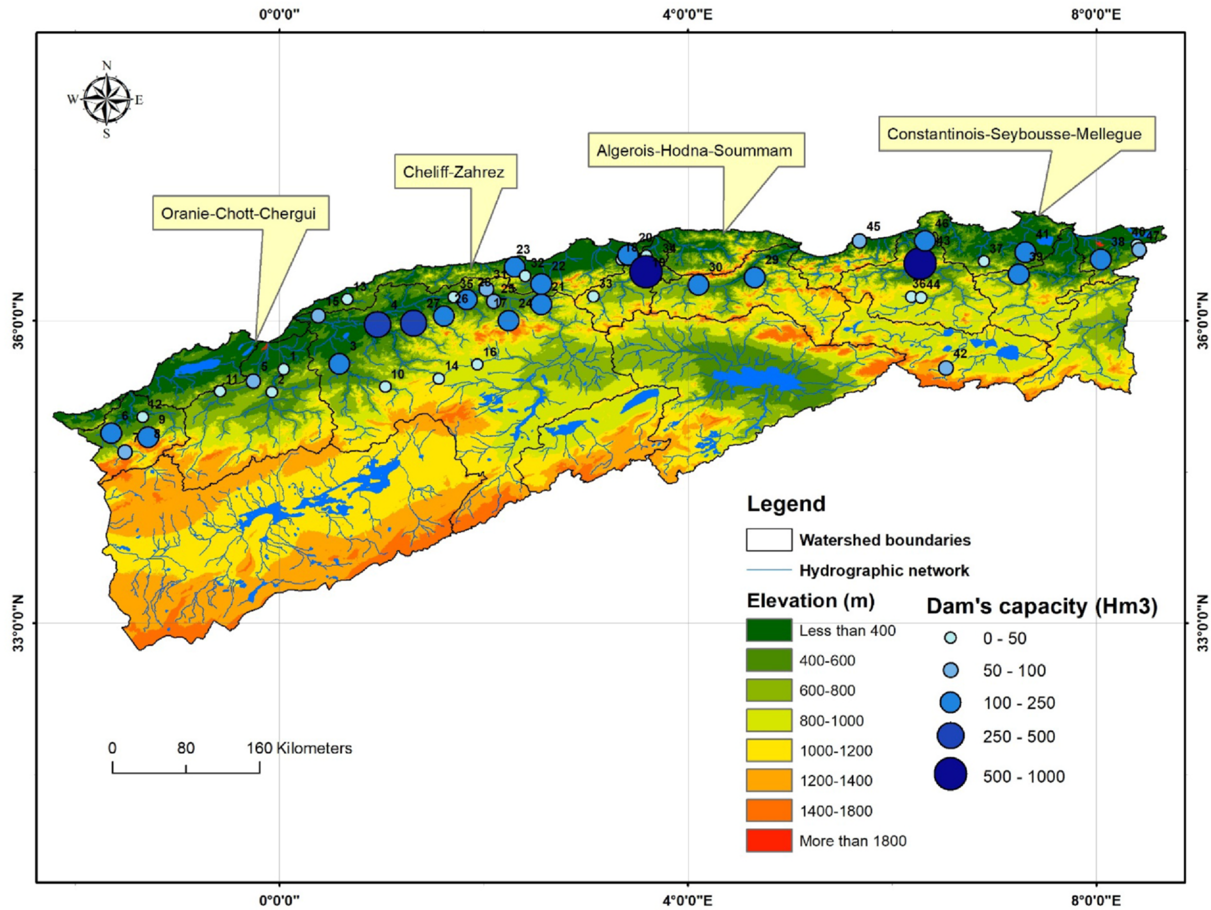

Fig. 1. (*continued*)

2016). Hence, the output can be assigned a constant value $y_{1d} = 1$ for $d = 1, \ldots, K$. As a result, each dam d aims to only minimize its inputs and, for efficiency evaluation, the input-oriented DEA model becomes the natural option (Oral et al., 2014).

The envelopment form of the input-oriented BCC model for estimating the technical efficiency θ of dam d is a LP model that writes as :

$$
\text{(DEA-WQI)}\quad
\begin{aligned}
& E^*_{dd} = \min \theta \\
& \text{Subject to} \\
& \textstyle\sum_{k=1}^{K} \lambda_{kd} s_{ik} \leq \theta s_{id} \qquad i = 1, \ldots, N && (4)\\
& \textstyle\sum_{k=1}^{K} \lambda_{kd} y_{1k} \geq y_{1d} && (5)\\
& \textstyle\sum_{k=1}^{K} \lambda_{kd} = 1 && (6)\\
& \lambda_{kd} \geq 0 \qquad k = 1, \ldots, K
\end{aligned}
$$

The efficiency E^*_{dd} of dam d represents the minimal radial reduction of inputs that is required to reach the efficiency frontier for a specified level of output y_{1d}. Dam d is efficient if $E^*_{dd} = 1$, otherwise, it is inefficient ($E^*_{dd} < 1$), i.e., it is not utilizing its inputs optimally. In practical words, if WQI_d represents the quality index of the water in dam d, $WQI_d = E^*_{dd}$ and, hence, the corresponding water risk index can be derived as $WRI_d = 1 - E^*_{dd}$. The higher the value of WRI_d, the more vulnerable the dam. Therefore, WQI_d appears undoubtedly as a valuable tool for rapid risk assessment, as it is amply stressed in the slack analysis section.

Constraints (4) and (5) indicate that reference points for dam d are linear combinations of efficient peers. By considering a single constant output, the set of constraints (5) reduces to a single constraint $\sum_{k=1}^{K} \lambda_{kd} \geqslant 1$. Since the latter includes the convexity constraint (6), it becomes redundant. Therefore, in terms of economies of scale, model DEA-WQI is the same under both constant and variable returns to scale assumptions.

Here, the vector $\boldsymbol{\lambda}_d = (\lambda_{1d}\ \lambda_{2d} .. \lambda_{Kd})\lambda$ provides the weights of the peers in producing the projection of dam d on the efficiency frontier. Let $\boldsymbol{\lambda}^*_d = (\lambda^*_{1d}\ \lambda^*_{2d} .. \lambda^*_{Kd})$ be the optimal vector. If $\lambda^*_{kd} > 0$ one can assert that dam k may serve as a benchmark (role model) for dam d and the reference set of dam d includes all potential benchmarks. Accordingly, the value of λ^*_{kd} can be regarded as the intensity of the endorsement expressed by the benchmark k towards the dam under evaluation d for achieving its efficiency target (Oukil and Govindaluri, 2017).

The benchmarking power B_d of a strongly efficient dam d is the number of times d appears as a benchmark of an inefficient or a weakly efficient dam. The higher the value of B_d the better its rank among the efficient dams.

Although able to classify the dams into efficient and inefficient, DEA-WQI model may fail to fully rank the dams by exhibiting more than one efficient dam, as it frequently occurs with standard DEA models (Oukil and Amin, 2015). To transcend this difficulty, we consider the benchmarking powers B_d of the efficient dams as an alternative to refining the ranking of the efficient dams.

3.4. Controlling water–related risks

As mentioned in section 3.3, WQI_d can be instrumented for rapid risk assessment through not only its derived water risk assessment index, but also the associated slack variables γ^*_{id}, which estimate the reduction of the ith input that is required from dam d to achieve full efficiency, i.e., mitigating as optimally as possible the risk impact. The slack variable γ^*_{id} is obtained from constraints (4) as follows.

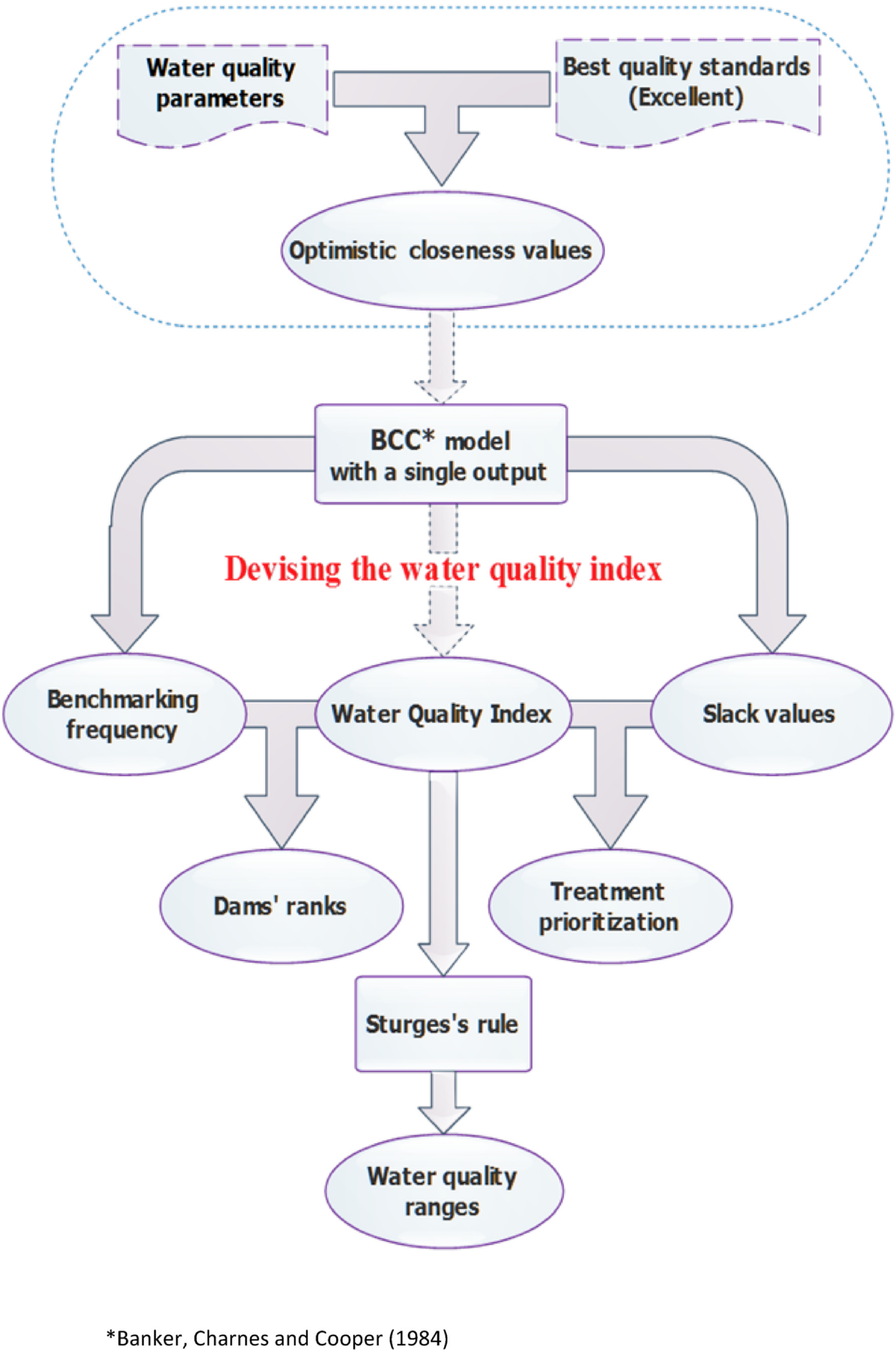

Fig. 2. Conceptual framework of the new WQI generation methodology. *Banker, Charnes and Cooper (1984).

Table 2
The standard ranges of water quality parameters (ANRH, 2009).

Parameter	Excellent	Acceptable	Poor	Unsuitable
pH	6.5–8.5	8.5–9	9–9.5	< 6.5 & > 9.5
TS (mg.L^{-1})	< 1000	1000–1200	1200–1600	> 1600
DO (%)	> 90	90–50	50–30	< 30
NO_3^- (mg.L^{-1})	< 10	10–20	20–40	> 40
NO_2^- (mg.L^{-1})	< 0.01	0.01–0.1	0.1–3	> 3
NH_4^+ (mg.L^{-1})	< 0.01	0.01–0.1	0.1–3	> 3
PO_4^{3-} (mg.L^{-1})	< 0.01	0.01–0.1	0.1–3	> 3
BOD (mg.L^{-1})	< 5	5–10	10–15	> 15
COD (mg.L^{-1})	< 20	20–40	40–50	> 50
OM (mg.L^{-1})	< 5	5–10	10–15	> 15

Table 3
Original values of the water quality parameters.

Dam	pH	TS	DO	NO_3^-	NO_2^-	NH_4^+	PO_4^{3-}	BOD	COD	OM
D_{01}	8.75	2400	57.30	10.0	0.840	0.390	0.240	5.9	29	15.6
D_{02}	8.44	1320	52.50	12.0	0.760	1.280	0.340	8.6	38	8.9
D_{03}	8.07	1660	69.10	7.0	0.190	0.130	0.110	6.9	38	8.8
D_{04}	8.01	1200	72.60	5.0	0.060	0.120	0.140	8.4	40	5.4
D_{05}	8.42	2200	45.10	11.0	1.110	0.410	1.080	12.8	58	22.0
D_{06}	8.79	1400	30.00	7.0	0.800	1.600	1.080	32.9	125	18.8
D_{07}	8.22	540	70.70	7.0	0.300	0.340	0.360	7.9	39	4.7
D_{08}	8.00	720	49.50	6.0	0.300	0.830	0.400	7.8	38	5.7
D_{09}	8.21	1100	71.50	5.0	0.140	0.270	0.170	9.8	48	5.8
D_{10}	8.06	960	73.70	8.0	0.320	0.280	0.270	6.6	29	7.7
D_{11}	8.20	3420	71.60	4.0	0.070	0.350	0.130	47.5	181	10.3
D_{12}	8.60	940	60.80	11.0	0.750	1.090	0.670	8.5	38	7.7
D_{13}	8.24	3040	77.40	7.0	0.250	0.240	0.270	7.0	30	8.2
D_{14}	8.38	1040	45.60	27.0	14.00	6.670	2.200	23.5	95	17.0
D_{15}	8.13	1900	75.90	6.0	0.050	0.160	0.400	6.4	30	7.1
D_{16}	9.01	2200	48.40	6.0	0.430	1.860	0.550	38.4	143	35.0
D_{17}	8.16	1980	73.90	4.0	0.050	0.190	0.260	5.2	29	6.3
D_{18}	8.30	756	71.90	2.7	0.268	0.235	0.337	10.0	30	8.3
D_{19}	8.20	1015	76.50	6.0	0.871	0.425	0.459	28.0	46	18.0
D_{20}	8.50	939	70.20	6.1	0.425	0.224	0.306	11.0	36	5.0
D_{21}	8.30	1890	78.70	5.2	0.223	0.500	0.306	7.0	35	8.6
D_{22}	8.30	974	68.80	13.8	0.449	0.500	0.306	9.0	25	9.5
D_{23}	8.60	687	54.50	5.8	0.110	0.200	0.214	6.0	20	5.0
D_{24}	8.30	1165	82.60	7.3	0.237	0.400	0.275	7.0	35	10.0
D_{25}	8.30	1593	93.20	5.4	0.220	0.330	0.918	7.0	35	7.5
D_{26}	8.30	997	77.40	1.8	0.137	0.124	0.551	13.0	25	5.0
D_{27}	8.30	1300	87.20	3.0	0.683	0.127	0.306	14.0	20	7.0
D_{28}	8.30	1185	85.00	4.9	0.696	0.200	0.367	12.0	26	7.8
D_{29}	8.40	388	60.30	4.6	0.137	0.300	0.153	6.0	26	6.0
D_{30}	8.60	519	55.80	4.2	0.343	0.360	0.122	11.0	33	10.0
D_{31}	8.30	465	88.70	3.5	0.172	0.100	0.306	5.0	29	5.0
D_{32}	8.30	812	68.50	5.0	0.069	0.230	0.398	8.0	30	6.0
D_{33}	8.70	578	47.20	8.9	0.823	1.450	0.490	13.0	39	10.5
D_{34}	8.30	979	61.90	5.5	0.274	0.200	0.122	6.0	25	12.0
D_{35}	8.30	927	82.10	3.9	0.233	0.215	0.796	12.0	33	6.0
D_{36}	7.80	1236	70.98	20.0	2.121	2.560	1.480	10.0	86	19.4
D_{37}	8.13	514	84.22	6.0	0.162	0.370	0.070	4.0	39	7.4
D_{38}	7.98	306	80.09	10.0	0.198	0.160	0.040	3.0	37	7.0
D_{39}	8.14	486	93.33	10.0	0.220	0.190	0.040	3.0	44	8.5
D_{40}	7.82	342	81.38	13.0	0.097	0.160	0.050	3.0	35	7.8
D_{41}	8.30	546	94.28	6.0	0.103	0.220	0.390	3.0	32	8.1
D_{42}	8.00	770	80.44	6.0	0.137	0.110	0.040	3.0	35	7.7
D_{43}	7.98	826	89.17	9.0	0.210	0.120	0.060	4.0	35	8.7
D_{44}	7.89	816	74.62	10.0	0.146	0.150	0.030	4.0	41	8.7
D_{45}	8.45	290	93.95	1.0	0.028	0.030	0.030	2.0	28	5.6
D_{46}	8.59	342	89.41	5.0	0.090	0.050	0.050	1.0	18	5.6
D_{47}	8.36	440	79.77	7.0	0.089	0.160	0.050	3.0	48	7.7
Avg	8.29	1109	71.65	7.3	0.650	0.570	0.380	10.0	43.7	9.5
Min	7.80	290	30.00	1.0	0.030	0.030	0.030	1.0	18.0	4.7
Max	9.01	3420	94.28	27.0	14.00	6.670	2.200	47.5	181.0	35.0
SD	0.25	703	15.02	4.5	2.030	1.050	0.410	9.4	31.8	5.6

Avg: Average; Min: minimum; Max: Maximum; SD: Standard Deviation

$$\gamma_{id}^{*} = E_{dd}^{*} s_{id} - \sum_{k=1}^{K} \lambda_{kd}^{*} s_{ik} \; i = 1, \ldots, M \quad (7)$$

If dam d is strongly efficient, $\gamma_{id}^{*} = 0$ for $i = 1, \ldots, N$ and $\lambda_d = \underline{1}$ where $\underline{1}$ is a vector with $\lambda_{kd}^{*} = 1$ and the remaining elements are zero. Conversely, dam d is weakly efficient if $E_{dd}^{*} = 1$ but some of the slack variables γ_{id}^{*} or all of them are strictly positive.

The importance of γ_{id}^{*} resides in the fact that it measures the required improvement of the water quality parameter i of dam d with reference to local benchmarks. Such an approach allows the evaluation to be confined into the hydrochemical context that is proper to the study area even if the background data, i.e., s_{id}, are based on WQS. Accordingly, the water risk mitigation is likely to be faster and cheaper provided that the thresholds induced by the benchmark's water quality parameters are more reachable than the standard quality ranges. On the other hand, risk ranking will be based on achievable targets rather than ideal guidelines.

4. Application and results' discussion

4.1. Data collection

Based on the ANRH plan, a sampling of water quality parameters is carried out monthly at several monitoring sites (dams). We were able to collect full data for 10 physicochemical parameters, over 11 months (January to November 2019), from 47 large dams (Appendix A1), distributed over the four hydrographic basin areas of the Tellian region as shown in Fig. 3.

The measured parameters include pH, Total Solids (TS), Dissolved Oxygen (DO), Nitrate (NO_3^-), Nitrite (NO_2^-), Ammonia (NH_4^+), Phosphate (PO_4^{3-}), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD) and Organic Matter (OM). All water samples were collected, stored, transported and examined by ANRH staff using the standard methods of Rodier et al. (2009).

Table 3 provides the original values of the water quality parameters measured over 11 months.

The observations in Table 3 reveal that the concentrations of basic elements, viz., pH, TS and DO, vary between 7.8 and 9.01, 290 and 3420 (mg/L), and 30 and 94.28%, respectively. The values of TS exceed the standards in 19.45% of the dams. It is known that TS is the result of dissolved, colloidal and suspended solids from minerals and organic matter in soils and living aquatic microorganisms and their decaying remains (Boyd, 2015; Hamil et al., 2018). Thus, the highest values of TS in this survey may be caused by agricultural runoff. Meanwhile, the organic pollution indicators, namely BOD, COD and MO, vary between 1 and 47.5 (mg/L), 18 and 181 (mg/L), and 4.7 and 35 (mg/L), respectively, with domestic wastewater discharges and industrial effluents possibly the main sources behind the increase of these parameters. The levels of chemical nutrients, i.e., NO_3^-, NO_2^-, NH_4^+ and PO_4^{3-}, fall within the ranges 1–27 (mg/L), 0.03–14 (mg/L), 0.03–6.67 (mg/L) and 0.03–2.2 (mg/L), respectively. The maximum values for NO_2^- and NH_4^+ are observed at D_{14}, i.e. "Dahmouni" dam, probably due to the excessive fertilization practices in the area. Here, it is

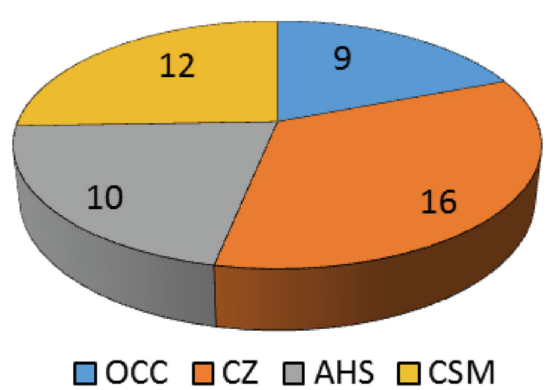

Fig. 3. Frequency of the dams per hydrographic basin.

important to remark that NO_3^-, NO_2^-, NH_4^+ belong to the same class and, practically, it might not be useful to consider all of them in the analysis. Such a step may also enable better DEA discrimination among the dams as a result of less input variables (Oukil and El-Bouri, 2019). However, it appears that, statistically, there is no strong evidence for discarding any of these variables. Indeed, the values of correlation coefficients between pairs of variables in the data sample (Hassan and Oukil, 2020) are $\rho(NO_3^-, NO_2^-) = 0.0213$, $\rho(NO_3^-, NH_4^+) = 0.2514$ and $\rho(NO_2^-, NH_4^+) = 0.4565$. With such a weak correlation, the ultimate option is to keep all these variables for the analysis (Hassan and Oukil, 2020).

Moreover, it is notable that, in spite of the importance of some physicochemical parameters, such as temperature, total dissolved solids (TDS), chlorophyll, and turbidity, in the analysis of surface water resources, their measures were available only for a limited number of dams.

4.2. Computation of the input variables

As noted in Section 4.1., our data sample was collected over 11 months (January to November 2019). Let x_{id}^t denote the value of the physicochemical parameters i associated to dam d, as measured in period t, for $i = 1, \ldots, 10;\ d = 1, \ldots, 47$ and $t = 1, \ldots, 11$. In order to guarantee the best treatment of dam's d water, we consider the least favorable sampling conditions, as reflected by the worst values of x_{id}^t viz. $x_{id} = worst(x_{id}^t)_{t=1,\ldots,11}$, where *worst* can be max or min, depending on the parameter$i$.

The measured values x_{id} of the water quality parameters are given in Table 3.

Table 4 provides a summary of the optimistic closeness values s_{id} corresponding to x_{id}.

The observed values reveal hyper concentrations of NO_2^-, NH_4^+, and PO_4^{3-}, exceeding even the acceptable range (0.1 mg/L) of the WQS for most dams. Therefore, chemical nutrients present the most prominent risk of contamination in the whole study area, followed by organic pollution such as BOD, COD, and OM and basic physicochemical parameters, i.e., DO and TS.

Again, we should note that the computation of the optimistic closeness values s_{id} is context-dependent. The values in Table 4 are based on drinking WQS and, hence, they are not necessarily the same if the study context is irrigation water performance where difference WQS are available (Zahedi, 2017).

4.3. Computation of the WQI

The DEA-WQI model has been solved to optimality by using IBM-ILOG CPLEX 12.4. For each dam d, we compute $WQI_d = E_{dd}^*$, the intensity values λ_{kd}^*, and the slack values γ_{id}^* for $i = 1, \ldots, 10$. The benchmarking results are shown in Table 5.

The average WQI is $\bar{WQI} = 66.06$, with a standard deviation $\sigma_{WQI} = 30.53$ revealing a high level of inefficiency among the dams. As bold-highlighted in Table 5, it appears that 10 dams out of 47 are strongly efficient, namely D_{04}, D_{22}, D_{23}, D_{26}, D_{27}, D_{29}, D_{31}, D_{34}, D_{45}, and D_{46} whereas D_{20} and D_{44} are weakly efficient. Indeed, in spite of having an efficiency score of 1, the slack values of the water quality parameters of D_{20} and D_{44} are not all zero (see, Table 7), suggesting that these dams are on the facets of the efficiency frontier and more improvement is possible by reducing one of the inputs corresponding to these positive slacks. All the remaining dams are inefficient and need to benchmark one of the strongly efficient dams to achieve better performance. For instance, D_{01} can benchmark D_{34}, D_{45}, and D_{46} with an intensity of 0.212, 0.133, and 0.655, respectively. The intensity of D_{46} being the highest indicates that the latter may be the best dam to benchmark for D_{01}. The third column in Table 5 presents the benchmarking powers of the dams, where D_{45} appears as the dominating benchmark, with a frequency of 36, followed by D_{34} and D_{26}. As stressed on Section 3.3, the benchmarking power can be useful to discriminate among the efficient dams, whose efficiency score is the same. A possible ranking of the dams is exhibited in the last column of Table 5. Accordingly, the water quality of D_{45} may be declared as the best, while the worst water, that is, the most vulnerable, seems to be D_{16}'s.

It is important to remark that the results provided in Table 5 are sample-based, i.e., if new dams are added or old dams become un-operational, a new ranking is likely to be generated. In each of these potential scenarios, the addition or the exclusion of dams leads to new solutions of DEA-WQI model that might be completely different.

Moreover, we need to stress the fact that the WQIs are produced for drinking water. If the study concern is irrigation water, different index values are possible since the input variables will be calculated using different WQS.

Table 4
Optimistic closeness values of the water quality parameters.

Dam	pH	TS	DO	NO_3^-	NO_2^-	NH_4^+	PO_4^{3-}	BOD	COD	OM
D_{01}	0.25	1400	32.7	0	0.830	0.38	0.230	0.9	9	10.6
D_{02}	0	320	37.5	2	0.750	1.27	0.330	3.6	18	3.9
D_{03}	0	660	20.9	0	0.180	0.12	0.100	1.9	18	3.8
D_{04}	0	200	17.4	0	0.050	0.11	0.130	3.4	20	0.4
D_{05}	0	1200	44.9	1	1.100	0.40	1.070	7.8	38	17.0
D_{06}	0.29	400	60.0	0	0.790	1.59	1.070	27.9	105	13.8
D_{07}	0	0	19.3	0	0.290	0.33	0.350	2.9	19	0
D_{08}	0	0	40.5	0	0.290	0.82	0.390	2.8	18	0.7
D_9	0	100	18.5	0	0.130	0.26	0.160	4.8	28	0.8
D_{10}	0	0	16.3	0	0.310	0.27	0.260	1.6	9	2.7
D_{11}	0	2420	18.4	0	0.060	0.34	0.120	42.5	161	5.3
D_{12}	0.10	0	29.2	1	0.740	1.08	0.660	3.5	18	2.7
D_{13}	0	2040	12.6	0	0.240	0.23	0.260	2.0	10	3.2
D_{14}	0	40	44.4	17	13.99	6.66	2.190	18.5	75	12.0
D_{15}	0	900	14.1	0	0.040	0.15	0.390	1.4	10	2.1
D_{16}	0.51	1200	41.6	0	0.420	1.85	0.540	33.4	123	30.0
D_{17}	0	980	16.1	0	0.040	0.18	0.250	0.2	9	1.3
D_{18}	0	0	18.1	0	0.258	0.23	0.327	5.0	10	3.3
D_{19}	0	15	13.5	0	0.861	0.42	0.449	23.0	26	13.0
D_{20}	0	0	19.8	0	0.415	0.21	0.296	6.0	16	0
D_{21}	0	890	11.3	0	0.213	0.49	0.296	2.0	15	3.6
D_{22}	0	0	21.2	3.8	0.439	0.49	0.296	4.0	5	4.5
D_{23}	0.10	0	35.5	0	0.100	0.19	0.204	1.0	0	0
D_{24}	0	165	7.40	0	0.227	0.39	0.265	2.0	15	5.0
D_{25}	0	593	0	0	0.210	0.32	0.908	2.0	15	2.5
D_{26}	0	0	12.6	0	0.127	0.11	0.541	8.0	5	0
D_{27}	0	300	2.80	0	0.673	0.12	0.296	9.0	0	2.0
D_{28}	0	185	5.00	0	0.686	0.19	0.357	7.0	6	2.8
D_{29}	0	0	29.7	0	0.127	0.29	0.143	1.0	6	1.0
D_{30}	0.10	0	34.2	0	0.333	0.35	0.112	6.0	13	5.0
D_{31}	0	0	1.30	0	0.162	0.09	0.296	0	9	0
D_{32}	0	0	21.5	0	0.059	0.22	0.388	3.0	10	1.0
D_{33}	0.20	0	42.8	0	0.813	1.44	0.480	8.0	19	5.5
D_{34}	0	0	28.1	0	0.264	0.19	0.112	1.0	5	7.0
D_{35}	0	0	7.90	0	0.223	0.21	0.786	7.0	13	1.0
D_{36}	0	236	19.02	10	2.111	2.55	1.470	5.0	66	14.4
D_{37}	0	0	5.78	0	0.152	0.36	0.060	0	19	2.4
D_{38}	0	0	9.91	0	0.188	0.15	0.030	0	17	2.0
D_{39}	0	0	0	0	0.210	0.18	0.030	0	24	3.5
D_{40}	0	0	8.62	3	0.087	0.15	0.040	0	15	2.8
D_{41}	0	0	0	0	0.093	0.21	0.380	0	12	3.1
D_{42}	0	0	9.56	0	0.127	0.10	0.030	0	15	2.7
D_{43}	0	0	0.83	0	0.200	0.11	0.050	0	15	3.7
D_{44}	0	0	15.38	0	0.136	0.14	0.020	0	21	3.7
D_{45}	0	0	0	0	0.018	0.02	0.020	0	8	0.6
D_{46}	0.09	0	0.59	0	0.080	0.04	0.040	0	0	0.6
D_{47}	0	0	10.23	0	0.079	0.15	0.040	0	28	2.7
Avg	0.03	303	18.66	0.80	0.64	0.56	0.37	5.51	23.74	4.46
Min	0	0	0	0	0.02	0.02	0.02	0	0	0
Max	0.51	2420	60	17	13.99	6.66	2.19	42.5	161	30
SD	0.10	560	14.58	2.90	2.03	1.05	0.41	9.04	31.74	5.60

Avg: Average; Min: minimum; Max: Maximum; SD: Standard Deviation

Table 5
Benchmarking results.

Dam	WQI_d^*	Reference set	B_d	Rank
D_{01}	0.2358	D_{34} (0.212), D_{45} (0.133), D_{46} (0.655)	0	41
D_{02}	0.3507	D_{27} (0.092), D_{29} (0.361), D_{34} (0.077), D_{45} (0.47)	0	36
D_{03}	0.4083	D_{27} (0.028), D_{34} (0.143), D_{45} (0.83)	0	35
D_{04}	**1**	**D_{04} (1)**	**1**	9
D_{05}	0.1683	D_{27} (0.123), D_{34} (0.208), D_{45} (0.669)	0	43
D_{06}	0.0585	D_{26} (0.052), D_{27} (0.001), D_{29} (0.092), D_{45} (0.666), D_{46} (0.188)	0	46
D_{07}	0.8457	D_{31} (1)	0	14
D_{08}	0.4492	D_{26} (0.097), D_{31} (0.378), D_{45} (0.524)	0	33
D_{09}	0.5606	D_{31} (0.253), D_{45} (0.747)	0	25
D_{10}	0.7463	D_{26} (0.102), D_{29} (0.157), D_{34} (0.221), D_{45} (0.52)	0	16
D_{11}	0.3000	D_{45} (1)	0	38
D_{12}	0.2703	D_{26} (0.09), D_{29} (0.206), D_{34} (0.016), D_{45} (0.387), D_{46} (0.3)	0	40
D_{13}	0.6371	D_{27} (0.112), D_{29} (0.075), D_{34} (0.196), D_{45} (0.618)	0	23
D_{14}	0.0950	D_{22} (0.107), D_{26} (0.152), D_{27} (0.013), D_{45} (0.729)	0	45
D_{15}	0.7653	D_{26} (0.116), D_{45} (0.884)	0	15
D_{16}	0.0583	D_{45} (0.896), D_{46} (0.104)	0	47
D_{17}	0.8555	D_{26} (0.003), , D_{29} (0.146), D_{45} (0.851)	0	13
D_{18}	0.6284	D_{26} (0.309), D_{29} (0.007), D_{34} (0.259), D_{45} (0.425)	0	24
D_{19}	0.2766	D_{26} (0.184), D_{27} (0.014), D_{34} (0.049), D_{45} (0.753)	0	39
D_{20}	1	D_{31} (1)	0	11
D_{21}	0.4625	D_{27}(0.084), D_{29}(0.12), D_{34}(0.051), D_{45}(0.745)	0	32
D_{22}	**1**	**D_{22} (1)**	**2**	8
D_{23}	**1**	**D_{23} (1)**	**1**	10
D_{24}	0.4626	D_{27} (0.09), D_{34} (0.113), D_{45} (0.797)	0	31
D_{25}	0.5333	D_{45} (1),	0	27
D_{26}	**1**	**D_{26} (1)**	**14**	3
D_{27}	**1**	**D_{27} (1)**	**12**	4
D_{28}	0.6911	D_{26} (0.122), D_{27} (0.426), D_{34} (0.026), D_{45} (0.426)	0	18
D_{29}	**1**	**D_{29} (1)**	**10**	5
D_{30}	0.3486	D_{34} (0.123), D_{45} (0.49), D_{46} (0.387)	0	37
D_{31}	**1**	**D_{31} (1)**	**5**	7
D_{32}	0.7309	D_{26} (0.23), D_{45} (0.77)	0	17
D_{33}	0.1963	D_{26} (0.071), D_{29} (0.177), D_{34} (0.071), D_{45} (0.245), D_{46} (0.436)	0	42
D_{34}	**1**	**D_{34} (1)**	**16**	2
D_{35}	0.5376	D_{26} (0.337), D_{45} (0.663)	0	26
D_{36}	0.1115	D_{27} (0.054), D_{34} (0.07), D_{45} (0.876)	0	44
D_{37}	0.4211	D_{45} (1)	0	34
D_{38}	0.6667	D_{45} (1)	0	19
D_{39}	0.6667	D_{45} (1)	0	20
D_{40}	0.5333	D_{45} (1)	0	28
D_{41}	0.6667	D_{45} (1)	0	21
D_{42}	0.6667	D_{45} (1)	0	22
D_{43}	0.5333	D_{45} (1)	0	29
D_{44}	1	D_{45} (1)	0	12
D_{45}	**1**	**D_{45} (1)**	**36**	1
D_{46}	**1**	**D_{46} (1)**	**7**	6
D_{47}	0.5000	D_{45} (1)	0	30

4.4. Spatial distribution of the WQI

To better understand the spatial distribution of water quality, the WQIs are projected onto pertaining hydrographic basins, i.e. OCC, CZ, AHS and CSM. The proportions of efficient and inefficient dams per watershed are shown in Fig. 4.

The figures reveal that half of the efficient dams are located in AHS basin, while the remaining efficient dams are equally distributed between CSM and CZ basins. Despite sharing the same proportion of efficient dams, CSM is ranked better than CZ due to higher average WQI, where $\bar{WQI}_{CSM} = 64.7$ and $\bar{WQI}_{CZ} = 64.1$. All OCC basin's dams are found inefficient, with $\bar{WQI}_{OCC} = 36$which may be enough evidence to consider OCC basin as the area with the poorest water quality. Meanwhile, AHS basin's water quality can be classified as the best with $\bar{WQI}_{AHS} = 71.8$.

Interestingly, the latter findings suggest that water quality may be proportionately linked to the rate of precipitation, as the amount of rainfall decreases from east to west (Meddi and Toumi, 2015; Tramblay et al., 2018). It is also known that Djurdjura and Edough massifs, which are located in AHS and CSM watershed respectively, receive most of the rainfall in the territory (Touazi et al., 2004). In addition to perceived water scarcity in the country, salinity, organic pollution, and nitrogen-phosphorus elements have played a major role in the degradation of water quality.

4.5. Setting water quality ranges

As with all WQIs already developed in the literature, determining the number and the range of water quality categories is an essential step for ranking water sources. For this purpose, we use Sturges's rule (1926) to determine the best number I of intervals needed to classify a data sample of size K, and defined as:

$I = 1 + 3.322\log_{10}(K)$ (8)

In our case study, $K = 47$ and, accordingly, the number of adequate classes for the sample of WQIs would be $I \approx 7$. Using the sample range of the WQIs defined as $R = \max_{d=1,\ldots,47}(WQI_d) - \min_{d=1,\ldots,47}(WQI_d)$, the approximate class width $acw = R/I$ takes the value 13.45% . Under these settings, the 47 WQIs can be classified into 7 groups with a frequency distribution of 5, 5, 5, 8, 8, 4 and 12 dams, respectively, as shown in Fig. 5.

Conventional WQIs such as CCME–WQI or NSF–WQI primarily used five (05) categories for assessing water quality. Based on the results of the Sturges's method and the latter perspective, the water quality categorization scheme of the 47 Algerian dams is depicted in Table 6 as well as Fig. 5.

The category *"Poor"* quality includes dams of groups 1 and 2, whose WQIs range is [0–32]. The *"Marginal"* category involves dams of groups 3 and 4 where WQIs fall within [33–60]. The *"Medium"* category comprises dams of groups 5 and 6, with WQIs ranging between 61 and 87. In the *"Good"* quality category, we find the weakly efficient dams of the group 7, viz. D_{20} and D_{44}, whereas all the strongly efficient dams are assigned to the *"Excellent"* category within the WQI range [88–100].

As shown in Fig. 6, the most vulnerable sites are located in the western part of Algeria, specifically in the OCC basin, which accounts for 50% of the total number of Poor quality dams.

Over more than twenty years of severe and persistent drought throughout the country, western Algeria has been the hotspot zone (Bouabdelli et al., 2020). As such, climate variability can be considered as one of the contributing factors to water quality deterioration (Soltani et al., 2020). Nonetheless, man-made practices have also played a key role in the current dire situation. According to Hamlat et al. (2014) and Djelita et al., (2016), uncontrolled industrial effluents and some agricultural practices are the main sources of pollution. These authors also report that a significant amount of wastewater is released without treatment from surrounding urban settlements. For instance, the wastewater discharge of Ain Temouchent and Tlemcen provincial cities into "Boughrara" and "Sikkak" dams in the "Tafna" sub-basin is estimated to 85,927.2 m^3/d (Agence de Bassin Hydrographique Oranais Chott Chergui ABHOCC, 2006a) . Meanwhile, the provinces of Mascara, Saïda and Sidi Bel Abbes have a sewage flow of about 126,916 m^3/d (Agence de Bassin Hydrographique Oranais Chott Chergui ABHOCC, 2006b), which is collected in the wadis of the "Macta" sub-basin and directed towards the reservoirs of Fergoug, Cheurfa and Sarno.

On another hand, Fig. 6 shows that 5 out of 10 excellent water quality dams are found in the AHS basin.

4.6. Shifting category

Water treatment may enable a dam to shift up to a better water quality level but it remains pertinent to estimate the extent of WQI improvement that would be required to reflect significant ranking shift. Although the answer to this question is case study dependent, we will try to develop an empirical response approach.

Let C_g denote the centroid of water quality category g, where g can

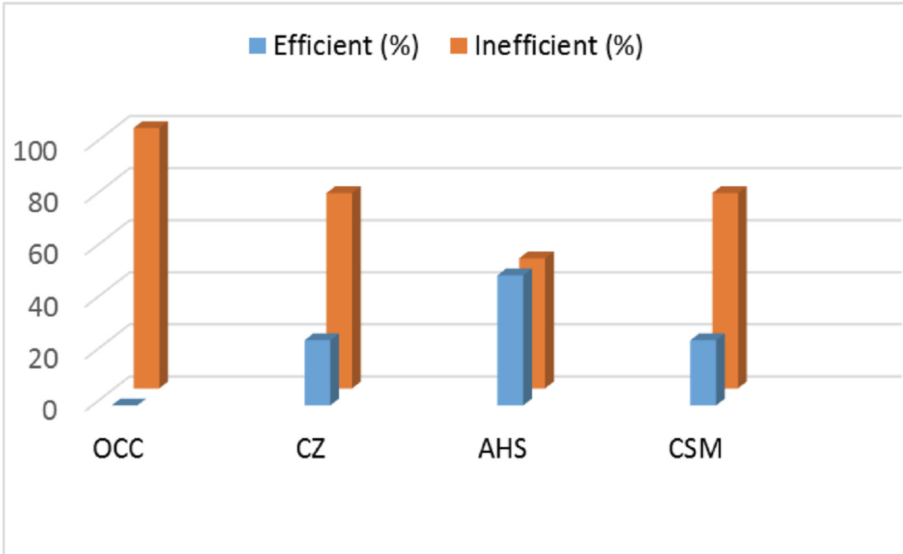

Fig. 4. Efficiency distribution of the dams over the major basins.

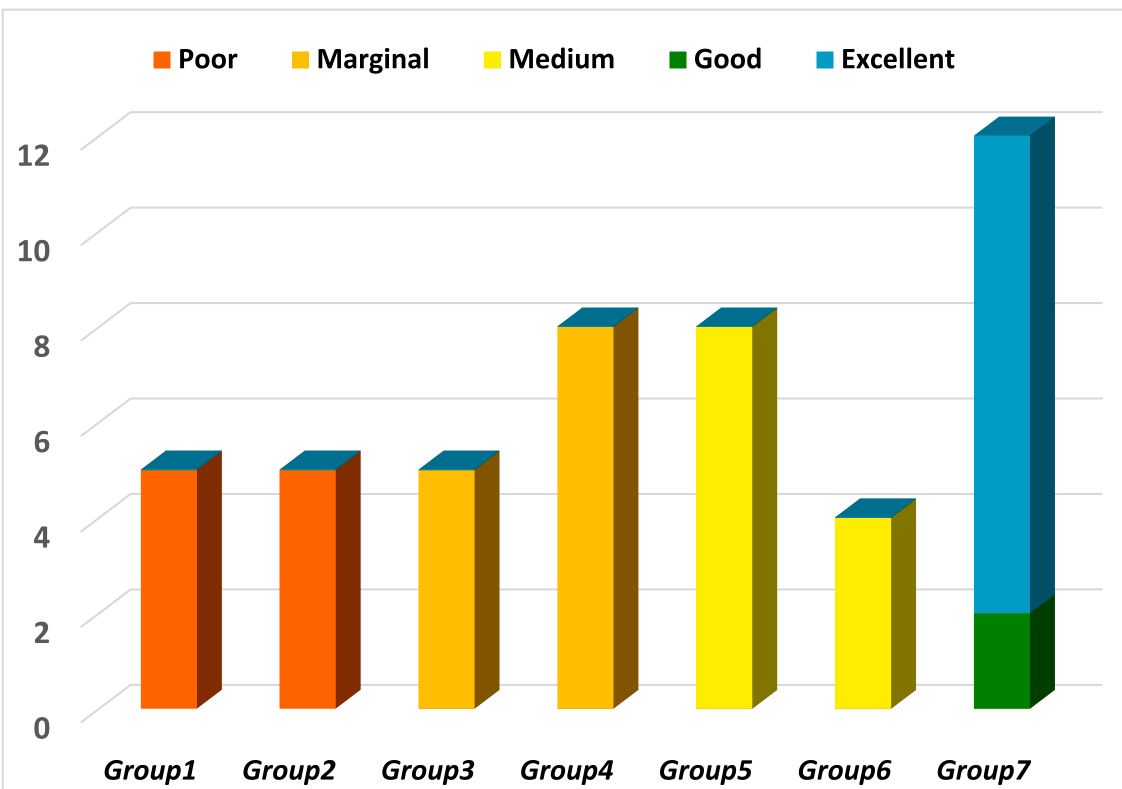

Fig. 5. Frequency distribution and water quality categorization of the dams.

Table 6
Water quality categorization of the dams.

WQI range	Category Rank	Included dams
88–100 [(a)]	Excellent	D_{04}, D_{22}, D_{23}, D_{26}, D_{27}, D_{29}, D_{31}, D_{34}, D_{45}, D_{46}
88–100 [(b)]	Good	D_{20}, D_{44}
61–87	Medium	D_{18}, D_{13}, D_{38}, D_{39}, D_{41}, D_{42}, D_{28}, D_{32}, D_{10}, D_{15}, D_{07}, D_{17}
33–60	Marginal	D_{30}, D_{02}, D_{03}, D_{37}, D_{08}, D_{21}, D_{24}, D_{47}, D_{25}, D_{40}, D_{43}, D_{35}, D_{09}
0–32	Poor	D_{16}, D_{06}, D_{14}, D_{36}, D_{05}, D_{33}, D_{01}, D_{12}, D_{19}, D_{11}

(a) Strongly efficient dams (b) Weakly efficient dams

Table 7
Descriptive summary of water quality classes.

Class	Number of dams	Min	Max	Centroid	S.D
Poor [0–32]	10	5.83	30	17.71	9.24
Marginal [33–60]	13	34.86	56.06	46.93	7.15
Medium [61–87]	12	62.84	85.55	71.39	7.63
Good [88–100]	2	100	100	100	0
Excellent [88–100]	10	100	100	100	0

Min: minimum; Max: Maximum; SD: Standard Deviation

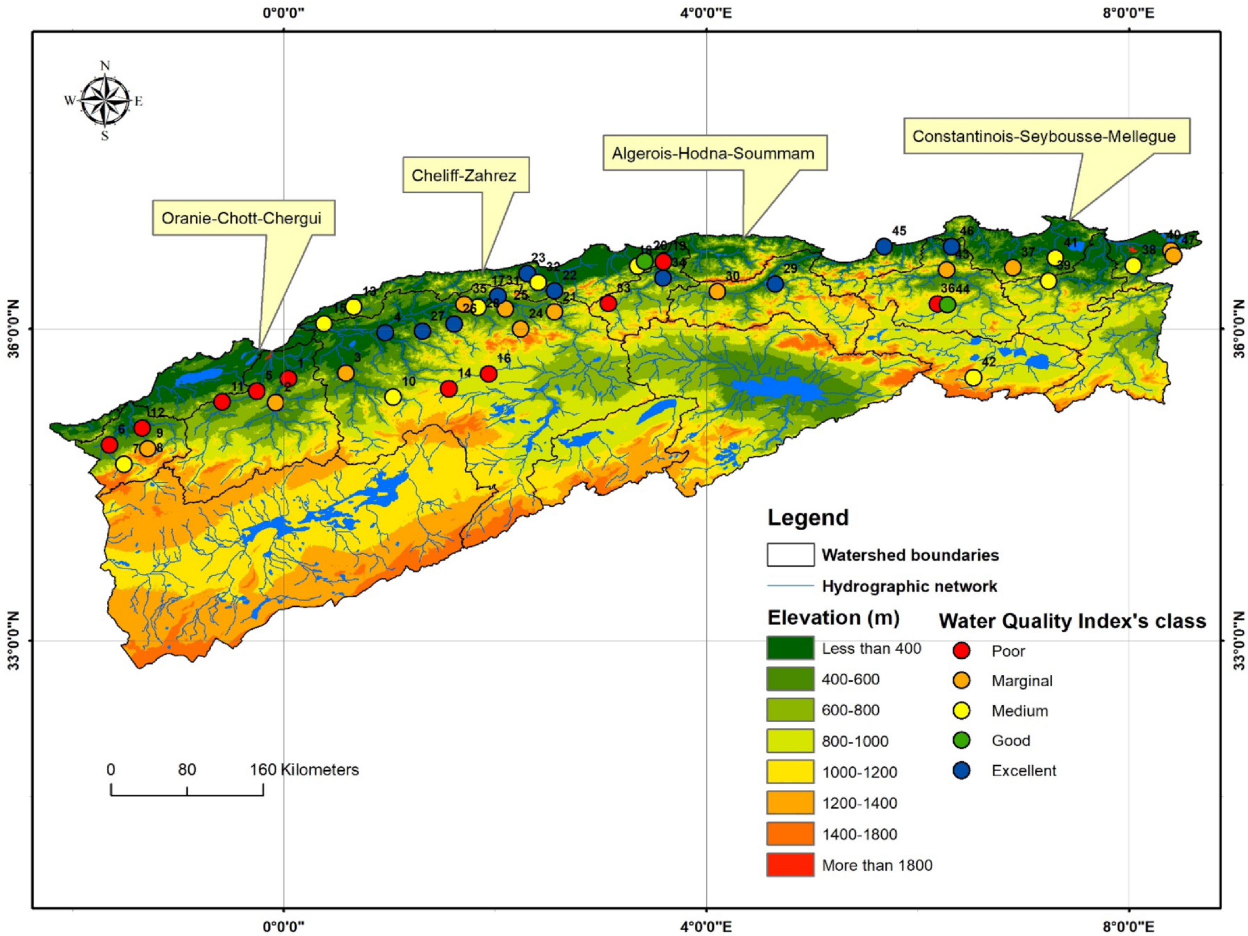

Fig. 6. Spatial variation of WQIs.

be 1: Poor, 2: Marginal, 3: Medium, 4: Good and 5: Excellent. The centroid C_g represents the average WQI of the dams within class g, as shown in Table 7.

Furthermore, the box plots in Fig. 7 exhibit a harmonic clustering for each category, which has been confirmed by a constant variance of the centroid from one class to another.

Accordingly, the $\overline{WQI}$ gaps between successive classes are $C_2 - C_1 = 29.22\%$, $C_3 - C_2 = 24.46\%$, $C_4 - C_3 = 28.61\%$. With the dams' frequencies almost equal across categories and the WQI deviation $\sigma_{WQI} = 30.53\%$ close to the $\overline{WQI}$ gaps, one can, empirically, hypothesize: a treatment process of dam d's water that achieves approximately 24% to 30% improvement in WQI_d is likely to shift dam d up to the next best category. Nevertheless, such a statement remains empirical and the figures may deviate from the suggested range with different water samples.

5. Water treatment prioritization

DEA-WQI model is not only a risk-ranking device but it has also great potential to support major decisions pertaining to water treatment of vulnerable dams.

Vulnerable dams include inefficient as well as weakly efficient dams. DEA-WQI model offers these dams the ability to improve their water quality indices by decreasing the current optimistic closeness values of related hydrochemical parameters. The slack values γ_{id}^* shown in Table 8 provide the required reduction associated to each parameter i for each dam$d$.

The importance of the slack values comes from the fact that it estimates the needed improvement with reference to the benchmarks rather than the water quality range. For instance, the slacks of dam D_{01} indicate that the latter must reduce the optimistic closeness values of TS, DO, NO_2^-, NH_4^+, PO_4^{3-} and OM with the corresponding amounts specified in Table 7, so that it can reach the quality level of its benchmarks. In other words, the implementation of such reductions on the values of the hydrochemical parameters will not only bring dam D_{01} on the efficiency frontier but also closer to the Excellent range of WQI.

Practically, reaching the former target (efficiency frontier) might be cheaper than the latter (Excellent range). This makes the proposed WQI reasonably more tractable.

However, handling all the parameters together may not be possible, due to budgetary constraints or other technical reasons. Under such circumstances, it becomes imperative to prioritize these parameters. i.e., "which parameter needs to be treated *prior* to others?"

Let c_{id} be the treatment cost per unit relating to the hydrochemical parameter i at dam d. Assuming that c_{id} is constant, i.e., it is the same for all parameters, the priority scale can be set starting from the smallest slack value γ_{id}^* to the highest, independently of the costs. Considering D_{01}, a valid treatment sequence is $PO_4^{3-} \rightarrow NH_4^+ \rightarrow NO_2^- \rightarrow$ OM $\rightarrow$ DO $\rightarrow$ TS. Here, priority is given to the parameter with the smallest γ_{id}^* as it enables reaching the efficiency frontier faster and cheaper.

In the event c_{id} values are different, the objective becomes finding a least-cost priority scale. In this scenario, parameters with smaller $c_{id}\gamma_{id}^*$ will be selected first.

However, if the managers aim to developing an optimal treatment scheme that involves simultaneously several hydrochemical parameters, the problem can be formulated as a knapsack problem with a budget limit Bd_d and decision variables z_{id} representing the required

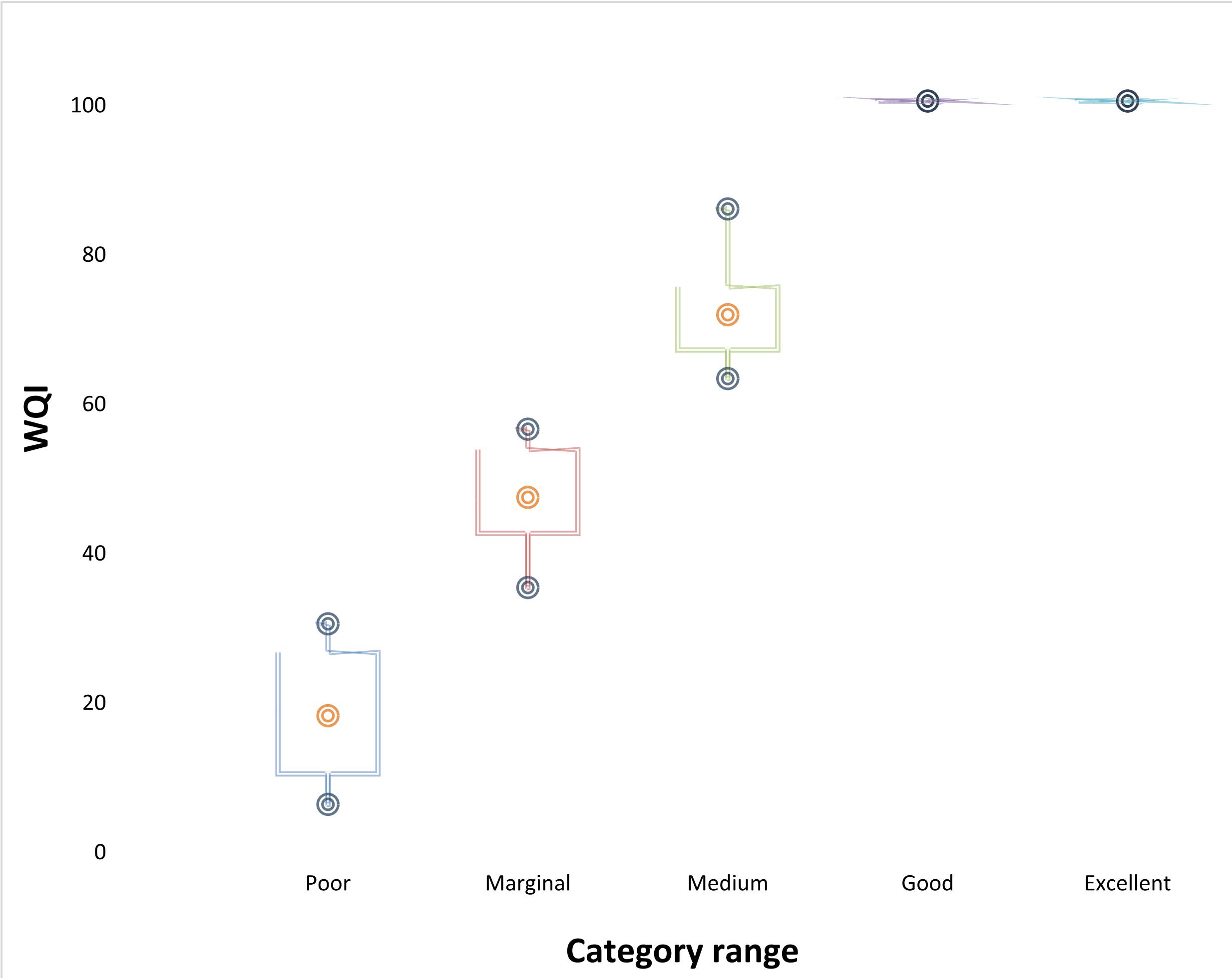

Fig. 7. Box plots of the dams WQI within each category range.

amount of slack value γ^*_{id} to target for each parameter i, $z_{id} \leqslant \gamma^*_{id}$, $i = 1, ...,10$.

6. Sensitivity analysis

Risk estimates are input-based, that is, any variation in the water quality parameters can affect not only the dams' risk indices but also the derived rankings. This aspect has been partly addressed from the slack perspective, which guarantees that the leading dams preserve their benchmarking status while seeking improvement of the vulnerable dams' performance.

Recall that the risk ranking model was assessed for the worst scenario, adopted as a standard for the whole study (refer to Section 4.2). Subsequently, as a part of the analysis of the model's sensitivity to input variations, we also examine the Best scenario, which is based on the best values of the water quality parameters observed over 11 months. Fig. 8 depicts the WQIs obtained under the two scenarios.

Under the Best scenario, 42.55%, of the dams are declared efficient, with a maximum score of 1, while 38.30% of the sites are highly vulnerable, exhibiting indices that tend towards zero. With > 80% of the dams clustered as strongly efficient or inefficient, the Best scenario's approach to risk assessment seems less realistic than the standard one, which stems from the assumption that the best values of the water parameters are achievable, i.e., the optimistic closeness values can hit their minima for all parameters. Here, the latter values were all zeros for 15 dams, which qualified as efficient. Furthermore, it should be noted that the Best scenario does not necessarily produce larger WQIs. Indeed, such a shift is witnessed for only 12 dams out of 47. While most of the dams identified as efficient under the standard scenario do preserve their status, the shift is rather extreme for D_{22} and D_{44}, recording, respectively, 9.09% and 2.41% as new WQIs instead of 100%. Similar extreme behaviour is visible for all 25 dams whose WQIs are deteriorating. Such an outcome is not surprising under the proposed DEA framework, where each dam's performance is evaluated relative to its peers and not as an absolute unit. Nonetheless, the remarkable discrepancies among the WQIs do enhance two aspects: (1) It is important to select carefully the standard scenario for the risk assessment process when dealing with panel data. (2) The WQIs yield through the Worst scenario are more balanced and, hence, more realistic, contrasted with the Best scenario.

Yet, uncertainty around the risk estimates can always be evaluated through an analysis of the risk rankings' sensitivity to the system's dynamism, where the observed input measures are fluctuating over the year. In line with this reasoning, we consider the measurements of the water quality parameters over the available samples (11 months), and we work out the corresponding WQIs using DEA-WQI model. The monthly WQIs are shown in Table 9.

Accordingly, it appears that D_{45} preserves its status as an efficient dam throughout all the study periods, except June and October, while D_{01}, D_{05}, D_{14}, D_{16} and D_{36} remain inefficient, recording the lowest WQI values. These results are consistent with the risk ranking approach developed in the study, which adopts the Worst scenario as a standard.

For a closer examination of the WQIs' sensitivity to monthly variations, the dams are ranked within each watershed, and the resulting

Table 8
Slack values of the hydro-chemical parameters.

Dam	pH	TS	DO	NO3	NO2	NH4	PO4	BOD	COD	OM
D_{01}	0	330.167	1.361	0	0.085	0.020	0.002	0	0	0.541
D_{02}	0	84.759	0	0.701	0.127	0.306	0.019	0	0	0
D_{03}	0	261.073	4.449	0	0.002	0.002	0	0.382	0	0
D_{05}	0	165.104	1.359	0.168	0.035	0	0.107	0	0	0.756
D_{06}	0	23.033	0	0	0	0.039	0	1.112	0	0.200
D_{07}	0	0	15.022	0	0.083	0.189	0	2.453	7.069	0
D_{08}	0	0	16.475	0	0.047	0.313	0	0.479	0	0
D_{09}	0	56.061	10.043	0	0.019	0.108	0	2.691	7.444	0
D_{11}	0	726	5.520	0	0	0.082	0.016	12.750	40.300	0.990
D_{12}	0	0	0	0.270	0.127	0.199	0.078	0	0	0
D_{13}	0	1266.266	0	0	0.006	0.062	0.088	0	0	0
D_{14}	0	0	0	1.208	1.241	0.547	0.076	0	0	0.196
D_{15}	0	688.760	9.333	0	0	0.084	0.218	0.146	0	1.077
D_{16}	0.020	69.907	2.362	0	0	0.086	0.009	1.946	0	1.148
D_{17}	0	838.360	9.408	0	0	0.094	0.174	0	0	0.456
D_{18}	0	0	0	0	0.046	0.046	0	0.407	0	0
D_{19}	0	0	0	0	0.179	0.068	0	4.716	0	2.773
D_{20}	0	0	18.500	0	0.253	0.124	0	6	7	0
D_{21}	0	386.454	0	0	0	0.157	0.074	0	0	0.573
D_{24}	0	49.252	0	0	0	0.132	0.067	0	0	0.865
D_{25}	0	316.267	0	0	0.094	0.151	0.464	1.067	0	0.733
D_{28}	0	0	0	0	0.157	0.054	0.043	0	0	0.647
D_{30}	0	0	8.244	0	0.044	0.073	0	1.969	0	0.357
D_{32}	0	0	12.810	0	0	0.119	0.144	0.349	0	0.269
D_{33}	0	0	0	0	0.070	0.187	0	0.751	0	0
D_{35}	0	0	0	0	0.065	0.059	0.227	1.067	0	0.140
D_{36}	0	10.063	0	1.115	0.165	0.247	0.122	0	0	0.481
D_{37}	0	0	2.434	0	0.046	0.132	0.005	0	0	0.411
D_{38}	0	0	6.607	0	0.107	0.080	0	0	3.333	0.733
D_{39}	0	0	0	0	0.122	0.100	0	0	8	1.733
D_{40}	0	0	4.597	1.600	0.028	0.060	0.001	0	0	0.893
D_{41}	0	0	0	0	0.044	0.120	0.233	0	0	1.467
D_{42}	0	0	6.373	0	0.067	0.047	0	0	2	1.200
D_{43}	0	0	0.443	0	0.089	0.039	0.007	0	0	1.373
D_{44}	0	0	15.380	0	0.118	0.120	0	0	13	3.100
D_{47}	0	0	5.115	0	0.022	0.055	0	0	6	0.750

rank patterns are presented in Figs. 9 to 12.

With only a few exceptions, the dams' rankings within each watershed are fluctuating over the year. However, Fig. 9 shows that, in OCC basin, D_{11} ranks first 5 times, whereas D_{06} and D_{12} rank last 3 times, with "Boughrara" dam, viz. D_{06}, the worst ranked in 11 months.

The situation is not so different in CZ watershed, as shown in Fig. 10. Here, D_{14} is the most vulnerable site in 8 out of 11 months, followed by D_{16}. The leading position is locally shared between D_{31} and D_{26}.

In AHS basin, Fig. 11 presents D_{19} as the worst and D_{29} as the best in most the year. In addition, D_{23} occupies almost permanently the second position, with slight jumps.

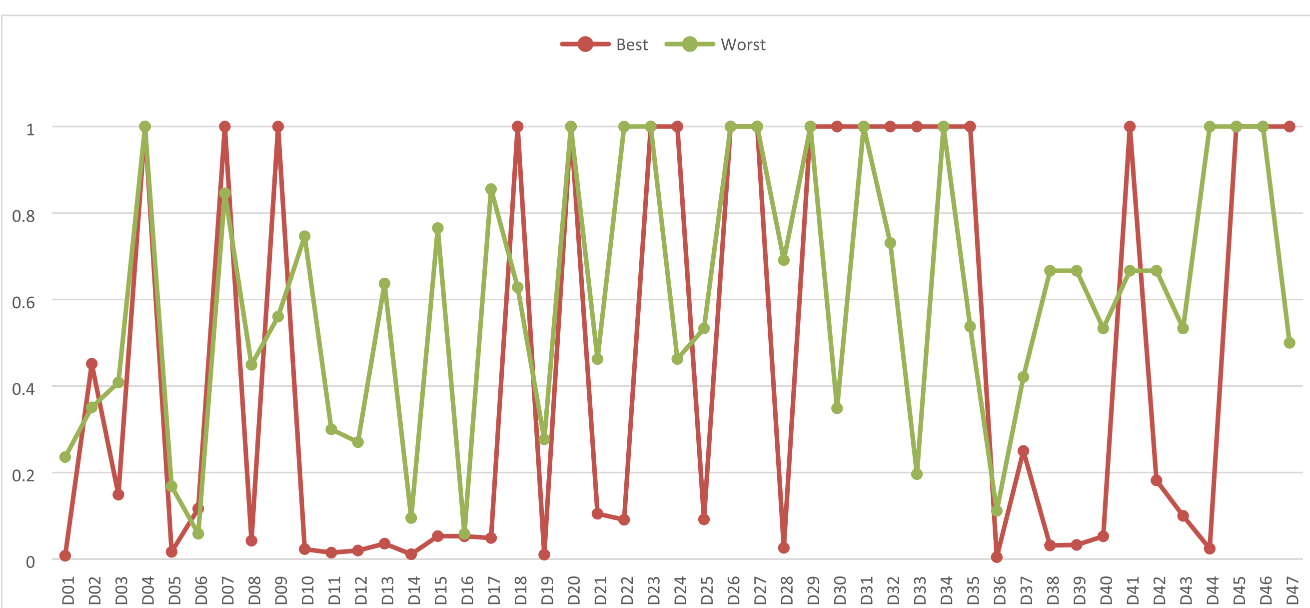

Fig. 8. Variation of WQIs in Best and Worst scenarios.

Table 9
Monthly WQIs of all dams.

Dam	January	February	March	April	May	June	July	August	September	October	November
D_{01}	0.0345	0.0455	0.0114	0.0798	0.0378	0.0282	0.1033	0.2727	0.2260	0.0337	0.0625
D_{02}	0.0720	0.0478	0.1146	0.0929	0.0151	0.0168	0.0512	0.2524	0.4678	0.0212	0.0526
D_{03}	0.0672	0.1395	0.0499	0.2788	0.2060	0.0599	0.2872	0.5478	0.3785	0.0973	0.0909
D_{04}	0.2584	0.3458	0.1170	0.4800	1	1	0.3906	0.3333	0.5101	1	0.2438
D_{05}	0.2644	0.0627	0.0435	0.1872	0.0502	0.0234	0.0792	0.0742	0.0751	0.0550	0.1667
D_{06}	0.0201	0.0568	0.0321	1	0.0106	0.0274	0.0509	0.1203	0.0633	0.0436	0.0556
D_{07}	0.0517	0.0911	0.0264	0.0919	0.0778	0.0476	0.3105	0.5000	0.7910	0.4667	0.0435
D_{08}	0.0369	0.2277	0.1174	0.3928	0.0115	0.0155	0.3072	0.2093	0.1644	0.0233	0.0709
D_{09}	0.2323	0.1500	0.0373	0.4545	0.0714	0.0547	0.4697	0.5000	0.9160	0.2011	0.6500
D_{10}	0.0603	0.1333	0.0220	0.1901	0.1182	0.0437	0.2059	0.3273	0.3063	0.0813	0.0659
D_{11}	0.3222	0.9000	0.0255	1	0.0294	0.0181	0.8043	0.0328	0.2841	0.0445	0.7800
D_{12}	0.0178	0.0209	0.0121	0.0370	0.0407	0.0705	0.0644	0.3333	0.4952	0.1679	0.0610
D_{13}	0.0718	0.0870	0.0243	0.1608	0.0739	0.0305	0.2576	0.2795	0.2383	0.0718	0.6500
D_{14}	0.0110	0.0113	0.0498	0.0120	0.0032	0.0057	0.0196	0.0335	0.0307	0.0136	0.0556
D_{15}	0.2250	0.4500	0.0564	1	0.3661	0.1272	0.4267	0.4737	0.4493	0.1537	0.9750
D_{16}	0.0909	0.2013	0.0185	0.1755	0.0489	0.0070	0.2908	0.0607	0.0272	0.0144	0.0123
D_{17}	0.4371	0.6667	0.0480	0.9730	0.0748	0.0415	1	0.4500	0.5686	0.0991	0.1667
D_{18}	0.5801	0.3566	1	1	1	0.2132	1	0.4000	0.6498	0.1489	0.1321
D_{19}	0.0354	0.0699	0.0122	0.0556	0.0290	0.0223	0.5310	0.2500	0.2323	0.0896	0.0455
D_{20}	1	0.4554	0.5840	0.3566	0.2350	0.0983	0.5853	0.2022	0.3309	0.3500	0.2000
D_{21}	0.3913	0.0636	0.0341	0.6441	0.4261	0.1244	0.0866	0.2308	0.1368	0.0766	0.0699
D_{22}	0.6322	0.0900	0.0176	0.2087	1	0.0681	1	0.6923	0.0859	0.0931	0.1064
D_{23}	1	1	0.4583	1	0.2867	0.3986	1	1	1	0.7000	0.1102
D_{24}	0.0431	0.1637	0.0435	0.6441	0.4227	1	1	0.4599	0.6872	1	0.1412
D_{25}	0.5244	0.6220	0.0755	0.1891	0.3333	0.2161	0.4688	0.8182	1	0.1892	0.0357
D_{26}	1	0.1754	1	1	0.5694	0.0674	1	1	1	1	0.2000
D_{27}	0.3667	0.1709	0.1786	0.4236	0.7961	0.1403	1	1	0.5455	1	0.2500
D_{28}	0.1084	0.1538	0.0840	0.2382	0.2350	0.0485	0.4398	0.2500	0.2060	0.1239	0.0526
D_{29}	1	1	1	0.5909	0.5734	0.1839	1	1	0.2069	1	1
D_{30}	1	0.4554	0.2078	0.2901	0.2000	0.1677	0.5263	0.5634	1	0.1750	0.1196
D_{31}	1	1	0.1111	1	1	1	0.2409	1	0.4918	1	0.2789
D_{32}	1	1	0.0760	0.6316	0.4713	0.0911	1	1	0.0573	0.0632	0.0626
D_{33}	0.0221	0.1935	0.0430	0.0721	0.1575	0.0337	0.0696	0.0590	0.5000	0.0132	0.0231
D_{34}	0.2991	0.1390	0.0610	1	0.0510	1	1	0.6061	0.6667	1	0.2500
D_{35}	0.2679	0.1786	0.5000	0.7611	0.1043	0.0709	0.9531	0.2687	0.0115	0.7000	0.0579
D_{36}	0.0501	0.0268	0.0169	0.0271	0.2277	0.0025	0.0557	0.0157	0.2567	0.0054	0.0050
D_{37}	0.6340	0.4493	0.3143	0.3985	0.2179	0.0720	0.4151	0.2500	0.3078	0.1429	1
D_{38}	0.2064	0.6538	0.0449	0.1249	0.0658	0.0414	0.3337	0.3000	0.3098	0.0852	0.0964
D_{39}	0.4478	0.1875	0.0418	0.1871	0.1614	0.0511	0.2717	0.5000	0.2640	0.1344	0.1000
D_{40}	0.1731	0.2222	0.0611	0.2759	0.1111	0.0527	0.3669	0.3214	0.7418	0.0859	0.1000
D_{41}	1	0.2727	1	0.3282	0.2500	0.0944	0.7333	0.1036	0.4133	0.3030	0.5052
D_{42}	0.2673	0.1986	0.2115	0.3949	0.1667	0.0683	0.2831	0.4500	0.2074	0.1012	0.1111
D_{43}	0.1974	0.4554	0.1000	0.1623	0.1192	0.0608	0.3301	0.2651	0.2457	0.1089	0.2600
D_{44}	0.1565	0.1809	0.0780	0.3274	0.2277	0.0661	0.2809	0.5000	1	0.0976	0.1429
D_{45}	1	1	1	1	1	0.2461	1	1	1	0.8974	1
D_{46}	0.4865	1	1	1	1	0.4583	0.4403	1	0.3351	0.3500	1
D_{47}	1	0.4000	0.0629	0.3146	0.1250	0.0686	0.0686	0.4286	0.9061	0.0768	0.1250

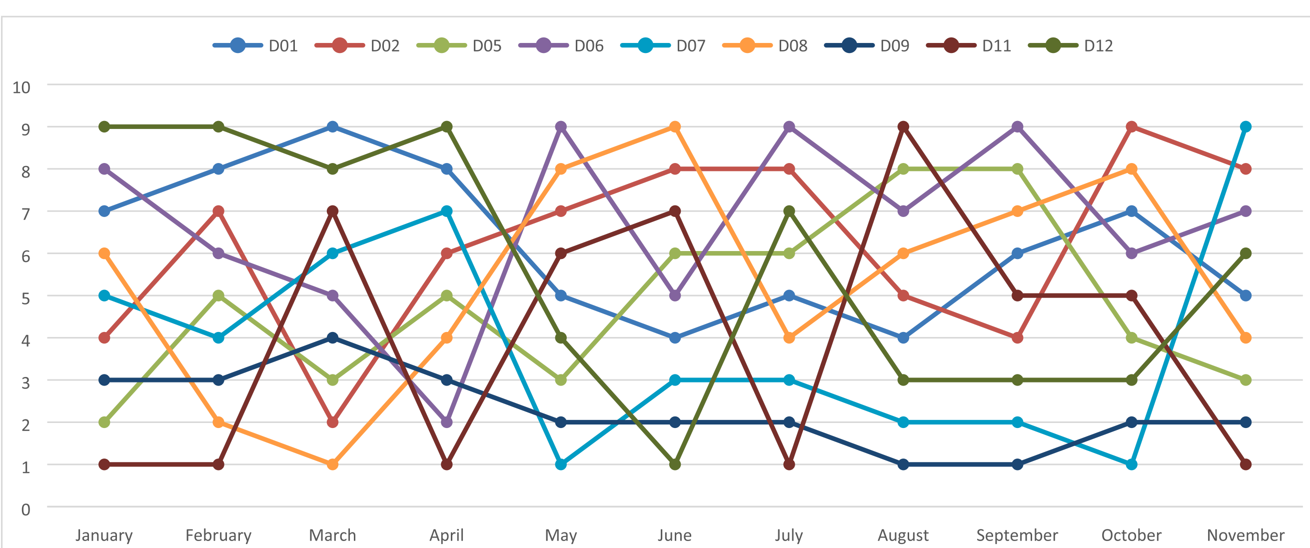

Fig. 9. Monthly ranking of dams within OCC watershed.

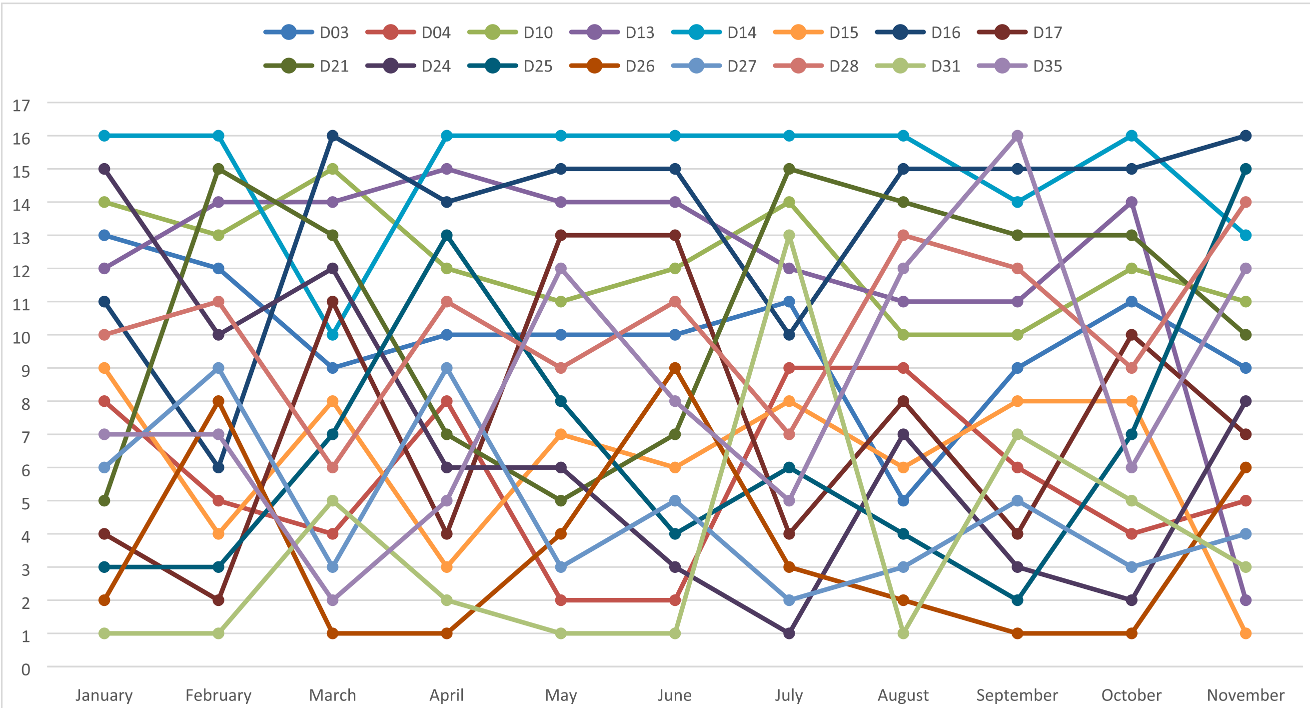

Fig. 10. Monthly ranking of dams within CZ watershed.

Fig. 12, depicting the monthly ranking patterns in CSM watershed, places D_{45} in the first position almost all the year, followed by D_{46}. On the other hand, D_{36} remains the most vulnerable over most of the months, except May and September.

Finally, the general picture over all the watersheds may suggest that short-range decisions relating to water treatment should better be based on monthly water samples, which is practically in line with the water system's dynamism. Tactical and strategic decision may however rely on the worst scenario.

7. Conclusion

Due to the continuous outbreak of various environmental polluting sources, improving water quality has turned out as one of the major challenges of water resource management experts, for better human health and aquatic life. In line with these concerns, there is a need to develop efficient evaluation systems for regular monitoring of water quality. Already established, WQI is a sophisticated tool that enables the overall state of water quality to be described by summarizing all the physicochemical parameters into a single value. In this paper, we devised a new WQI based on a DEA model, where the input variables, identified as "optimistic closeness values", are ingeniously derived from the values of the hydrochemical parameters.

The new methodology was applied on a dataset of 47 dams, described with 10 physicochemical parameters, and located over the four main Algerian hydrographic basins. i.e., OCC, CZ, AHS and CSM. The selected dams were classified into five distinct water quality categories. The inefficient dams fell under "Poor", "Marginal" and "Medium" water quality categories, with the proportions 21.27%, 27.66% and 25.53% of the total number of dams, respectively. Meanwhile, weakly and

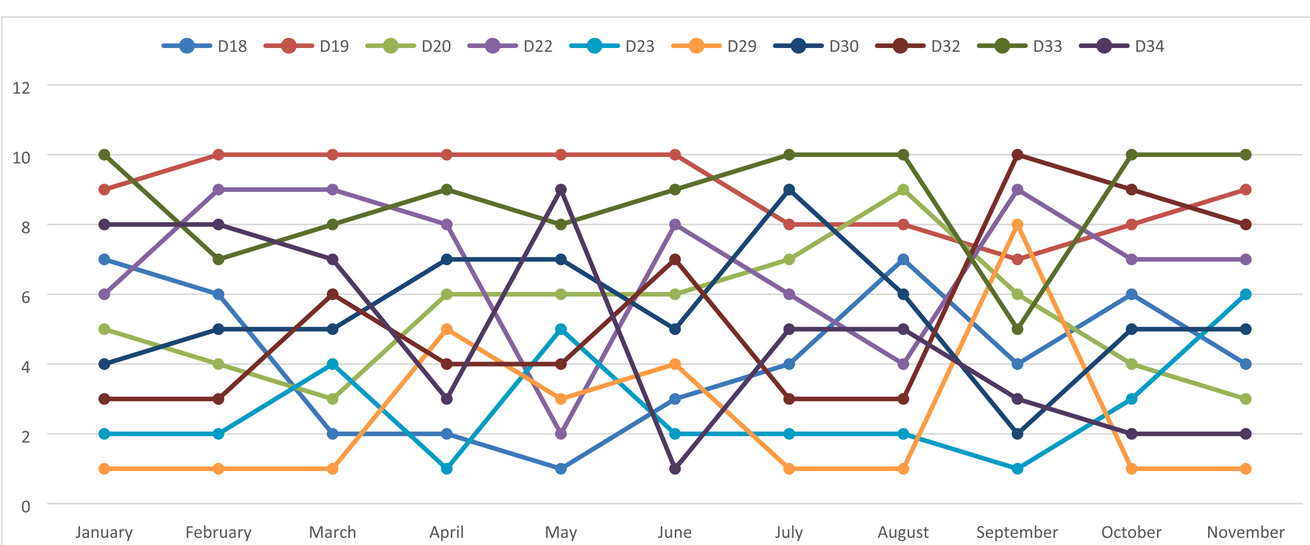

Fig. 11. Monthly ranking of dams within AHS watershed.

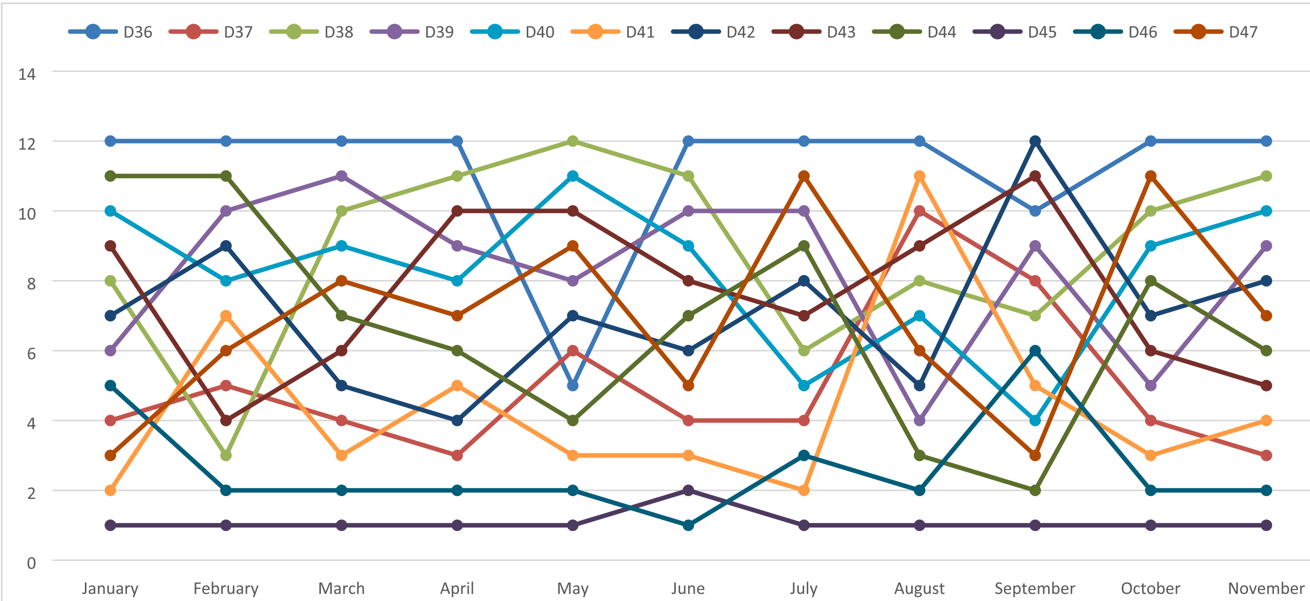

Fig. 12. Monthly ranking of dams within CSM watershed.

strongly efficient dams, which represent 4.25% and 21.27% of all dams, belong, respectively, to "Good" and "Excellent" categories. Subsequently, the spatial ranking of water quality in related watersheds can be depicted in the dominance scheme AHS≻CSM≻CZ≻OCC with average WQIs of 71.8 > 64.7 > 64.1 > 36. The best water quality is found at the "Kissir" dam, in CSM basin, with a $WQI = 100$, while "Bougara" dam, located in CZ basin, hosts the worst water, whose WQI is 5.83. Based on previous studies, the water quality of Algerian dams suffers mainly from uncontrolled municipal and industrial wastewater effluents and the impact of agricultural fertilization practices. Thus, it is interesting to note that the poorest water quality characterizes the western region and, hence, can be interpreted by the rate of precipitation due to the impact of climate change.

In addition, another virtue of DEA-WQI model resides in its ability to produce slack values, which provide useful measures for the reduction of input required from inefficient dams to reach the efficiency level of their benchmarks. In other words, the use of these values can help specialists to prioritize the hydrochemical parameters for less water treatment costs. Thus, the proposed methodology can be useful for fast assessment of risks concomitant with certain pollutants/pathogens, and serve as a basis for a more elaborate risk assessment.

It is noteworthy that, in spite of satisfying the basic dictum of an input, the newly developed variable, viz. optimistic closeness value, cannot, practically, be fully treated as a resource. For instance, considering possible merger of water samples (Amin and Oukil, 2019a), these inputs can neither be cumulated together nor be shared among water samples. Therefore, we believe that new research perspectives may focus on extending the new variable to other water quality assessment contexts.

Other research venues may explore the application of DEA models with missing data (Aksezer and Benneyan, 2010; Azizi, 2013; Badrizadeh and Paradi, 2020) to allow all hydrochemical parameters to be included in developing the WQI even if the full data may be available only for a few dams in the study sample. Another venue may investigate other models to refine the ranking of the dams, such as DEA bootstrap (Sow et al., 2016), DEA cross-efficiency (Oukil, 2018) and DEA super efficiency (Andersen and Petersen, 1993) commonly adopted to overcome the multiple occurrence of efficient units. More on these techniques along other DEA ranking models can be found in (Oral et al., 2015), (Aldamak and Zolfaghari, 2017), (Amin and Oukil, 2019b), (Oukil, 2019), (Banihashemi and Khalilzadeh, 2020) and (Oukil, 2020).

CRediT authorship contribution statement

Ahmed Amin Soltani: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualization. **Amar Oukil:** Conceptualization, Methodology, Validation, Formal analysis, Writing - original draft. **Hamouda Boutaghane:** Supervision, Project administration, Writing - review & editing. **Abdelmalek Bermad:** Supervision, Project administration, Writing - review & editing. **Mohamed-Rachid Boulassel:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106952.

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