PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
MOHAMED BOUDIAF UNIVERSITY OF M'SILA
FACULTY OF TECHNOLOGY
DEPARTMENT OF HYDRAULIC

Serial number: ..……………………
Registration number: **D.HYD3C/02/17**

1985
جامعة محمد بوضياف - المسيلة
Université Mohamed Boudiaf - M'sila

Contribution to the study of dams' water quality in Algeria

A thesis submitted to the Department of Hydraulic in fulfillment of the requirements for the degree of Ph.D. in Hydraulic Sciences
(Doctorat of 3rd cycle LMD)

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2020/2021

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Abstract

Algeria has always experienced a shortage of water resources in recent decades, and the situation has gotten worse when water quality has reached high levels of deterioration. The main objective of this thesis is to evaluate the surface water quality of a large number of Algerian dams in order to identify the most contaminated areas of the country and the factors that may lead to that. The present contribution has been divided into two-fold. The first study is devoted to assessing the water quality of forty-seven (47) dams, described with 10 Physico-chemical parameters, during 11 months (2019), and located over the four principal northern watersheds using a newly developed Water Quality Index based on the Data Envelopment Analysis (DEA-DQI) approach. The results of the proposed index revealed that 21.27%, 27.66%, 25.53%, 4.25%, and 21.27% of all dams are classified as " Poor", "Marginal", "Average", "Good", and "Excellent" water quality, respectively. The best water quality is found in the "Kissir" dam and the worst one in the "Bougara" dam. It is noteworthy that the dams with the worst water quality are located in the Oranie-Chott-Chergui watershed (OCC), in the western region, due to uncontrolled municipal-industrial discharges and agricultural fertilization practices. These results can also be interpreted by the agent of drought due to the impact of climate change. Among all the selected dams, Beni Haroun (BH) dam has been studied separately as a specific case in the second part of our contribution, given its major importance in the country. Under the same framework of an integrated approach with a dataset of 22 parameters observed during 11 years (2000-2010), several methods were employed, including the Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI), Principal Component Analysis and Factor Analysis (PCA/FA), K-means clustering and Ordinary Least Squares (OLS) to perform a comprehensive assessment of the water quality of BH dam and its upstream viz. Wadi Rhumel (WR). CCME-WQIs showed that BH dam is characterized by "Poor" water quality for drinking, irrigation, industry, and aquatic life, with indices of 17, 40, 42, and 32, respectively. Besides, K-means algorithm shows a clear similarity in water quality between BH dam and WR, which indicates it is the main pollution source of the dam's water. PCA/FA found that the water quality of BH dam is influenced by two major pollution factors: (i) natural processes and (ii) non-point source anthropogenic pollution. The most impressive finding of such a study is certainly the positive trend in WQIs using OLS, which is rather promising.

Keywords: *Surface water; Water quality; WQI; Dam; Beni Haroun; Pollution; Algeria.*

ملخص

لطالما عانت الجزائر من نقص فادح في الموارد المائية في العقود الأخيرة ، وازداد الوضع سوءًا حينما حققت جودة المياه مستويات عالية من التدهور. الهدف الرئيسي من هذه الأطروحة هو تقييم جودة المياه السطحية لعدد كبير من السدود الجزائرية من أجل تحديد المناطق الأكثر تلوثًا في البلاد والعوامل التي قد تؤدي إلى ذلك. تم تقسيم المساهمة الحالية إلى شقين. الدراسة الأولى تم تخصيصها لتقييم جودة مياه سبعة وأربعين (47) سدا ، ممثلة بعشر معايير فيزيوكيميائية ، رصدت خلال 11 شهرًا من عام 2019، تقع في الأحواض الشمالية الرئيسية الأربعة باستخدام مؤشر جودة المياه المطور حديثًا على أساس على نهج تحليل غلاف البيانات (DEA-WQI). أظهرت نتائج المؤشر المقترح أن 21.27٪ و 27.66٪ و 25.53٪ و 4.25٪ و 21.27٪ من إجمالي السدود تصنف على أن مياها فقيرة ، وهامشية ، ومتوسطة ، وجيدة ، وممتازة الجودة ، على التوالي. أفضل نوعية مياه توجد في سد "كيسير" وأسوأها في سد "بوقرة". يشار إلى أن السدود ذات الجودة المائية الأسوأ تقع في حوض أوراني - شط - شرقي (OCC)، في غرب البلاد، بسبب التصريفات الصناعية البلدية غير الخاضعة للرقابة وممارسات التسميد الزراعي. يمكن أيضًا تفسير هذه النتائج من خلال قلة الأمطار الناتجة عن تأثير تغير المناخ. من بين جميع السدود المختارة ، تمت دراسة سد بني هارون بشكل منفصل كحالة خاصة في الجزء الثاني من مساهمتنا ، نظرًا لأهميته الرئيسية في البلاد. ضمن إطار نهج موحد لعدة طرق كمؤشر مجلس الوزراء الكندي جودة المياه البيئية (CCME-WQI), تحليل المكونات الرئيسية وتحليل العوامل (PCA/FA), K-means clustering والمربعات الصغرى العادية (OLS) مع قاعدة بيانات تتكون من 22 معلمة رصدت خلال 11 عامًا (2000-2010) ، تم إجراء تقييم شامل لنوعية المياه في سد بني هارون و واد الرمال (WR). أظهر CCME-WQIs أن سد بني هارون يتميز بجودة مياه "رديئة" سواء كان إستخدامه للشرب والري والصناعة والحياة المائية ، وذلك بمؤشرات تقدر بـ 17 و 40 و 42 و 32 على التوالي. إلى جانب ذلك ، تُظهر خوارزمية K-means تشابهًا واضحًا في جودة المياه بين سد بني هارون ومنبعه WR ، مما يدل على أنه مصدر التلوث الرئيسي لمياه السد. وجدت PCA / FA أن جودة المياه في سد بني هارون تأثرت بعاملين رئيسيين للتلوث هي: (1) العمليات الطبيعية و (2) التلوث البشري المصدر غير المحدد. النتيجة الأكثر إثارة للإعجاب في مثل هذه الدراسة هي بالتأكيد الاتجاه الإيجابي في WQIs باستخدام OLS ، وهو أمر واعد إلى حد ما.

الكلمات المفتاحية: المياه السطحية, نوعية المياه, مؤشر نوعية المياه, السد , بني هارون, التلوث, الجزائر.

Résumé

Dans les dernières décennies, l'Algérie a toujours connu une pénurie de ressources en eau, et la situation s'est aggravée lorsque la qualité de l'eau a atteint des niveaux élevés de détérioration. Le principal objectif de cette thèse est d'évaluer la qualité des eaux de surface d'un grand nombre de barrages algériens afin d'identifier les zones les plus contaminées du pays et les facteurs qui peuvent y conduire. La présente contribution a été divisée en deux parties. La première étude est consacrée à l'évaluation de la qualité de l'eau de quarante-sept (47) barrages, décrits avec 10 paramètres physico-chimiques, pendant 11 mois (2019), et situés sur les quatre principaux bassins versants du nord en utilisant un Indice de Qualité de l'Eau nouvellement développé basé sur l'approche d'Analyse par Enveloppement des Données (AED-IQE). Les résultats de l'application de l'indice proposé ont révélé que 21,27 %, 27,66 %, 25,53 %, 4,25 % et 21,27 % de l'ensemble des barrages sont classés comme ayant une qualité d'eau " Mauvaise ", " Marginale ", " Moyenne ", " Bonne " et " Excellente ", respectivement. La meilleure qualité d'eau se trouve dans le barrage de "Kissir" et la plus mauvaise dans celui de "Bougara". Il convient de noter que les barrages dont la qualité de l'eau est la plus mauvaise sont situés dans le bassin versant de l'Oranie-Chott-Chergui (OCC), dans la région ouest, en raison de rejets municipaux-industriels non contrôlés et de pratiques de fertilisation agricoles. Ces résultats peuvent également être interprétés par l'agent de la baisse du taux de précipitation due à l'impact du changement climatique. Parmi tous les barrages sélectionnés, le barrage de Beni Haroun (BH) a été étudié séparément comme un cas spécifique dans la deuxième partie de notre contribution, vu son importance majeure dans le pays. Dans le même contexte d'une approche intégrée avec une base de données de 22 paramètres observée durant 11 ans (2000-2010), plusieurs méthodes ont été employées, notamment l'indice de qualité des eaux du Conseil Canadien des Ministres de l'Environnement (IQE-CCME), l'Analyse en Composantes Principales et l'Analyse Factorielle (ACP/FA), le clustering de K-means et l'Analyse des Moindres Carrés simples (AMC) pour effectuer une évaluation exhaustive de la qualité des eaux du barrage de BH et de son cours d'eau Oued Rhumel (ORh). Les IQE du CCME ont montré que le barrage de BH est caractérisé par une qualité d'eau "Médiocre" pour la potabilité, l'irrigation, l'industrie et la vie aquatique, avec des indices de 17, 40, 42 et 32, respectivement. En outre, l'algorithme de K-means montre une claire similitude dans la qualité de l'eau entre le barrage de BH et son cours d'eau (ORh), ce qui indique qu'il s'agit de la principale source de pollution de l'eau du barrage. ACP/FA a permis de constater que la qualité de l'eau du barrage de BH est influencée par deux facteurs de pollution majeurs: (i) les processus naturels et (ii) la pollution anthropique non ponctuelle. La conclusion la plus impressionnante d'une telle étude est certainement la tendance positive des IQE en utilisant les moindres carrés simples, ce qui est plutôt prometteur.

Mots clés *: Eau de surface ; Qualité de l'eau ; IQE ; Barrage ; Beni Haroun ; Pollution ; Algérie*

Acknowledgments

First and foremost, I am thankful to ***ALLAH ALMIGHTY*** *for blessing me with sound health, strength, and ability to perform and complete this thesis in the best manner. Without the aid of* ***ALLAH****, I could not do my research at all.*

I would like to express my sincere gratitude to my supervisor, ***Prof. Abdelmalek BERMAD*** *for his support, encouragement, valuable advice throughout all these years. His great wisdom and experience in the research field made the work very pleasant and easier. Indeed, I was honored and privileged to work under his supervision.*

I am very grateful to express my special thanks to my Co-supervisor, ***Dr. Hamouda BOUTAGHANE*** *for giving me the right guidance and motivation to accomplish this thesis. I greatly appreciate his positive comments, his heartening words, and his willingness to help me any time throughout this endeavor.*

I would like to extend my deepest gratitude to my Co-supervisor abroad ***Prof. Osman ABDALLA*** *for hosting me in* ***W****ater* ***R****esearch* ***C****enter at* ***SQU*** *in* ***Oman*** *with all modesty despite his multiple responsibilities. A huge thank goes also to* ***Prof. Amar OUKIL*** *who helped me to achieve my goal through his priceless collaboration, direction, and availability. I wish to thank* ***Prof. Mohamed-Rachid BOULASSEL*** *for his great attention and fatherly advice offered to me during my period of scholarship residency.*

I wish to acknowledge the Chairman of the examination committee, ***Pr. Mahmoud HASBAIA*** *for giving me insightful advice, for accompanying and supporting me along with my research work, " Thank you so much " does not seem to be enough for him, but it is said from the bottom of my heart!. I would also like to thank the members of my oral examination committee,* ***Pr. Belkacem MERZOUK*** *and* ***Dr. Mostefa DOUGHA****, from M'sila University, and* ***Dr. Abdelouahab LEFKIR*** *from "École Nationale supérieure des Travaux Publics", Algiers for accepting the examination of this thesis.*

*My gratitude also goes to "Agence Nationale des Ressources Hydraulique" (****ANRH****) for providing me the necessary data for my research work as well as the financial support provided by the* ***M****inistry of* ***H****igher* ***E****ducation and* ***S****cientific* ***R****esearch for my scholarship, within the framework of " Programme National Exceptionnel (****PNE****) ".*

Finally and most importantly, I would like to express my deepest gratitude to all my family, my dearest parents, my brother, and my sister, may Allah preserve them, who have made me who I am today. My gratitude also goes to all my colleagues and friends without exception.

«Ahmed Amin»

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Introduction

Water is the most essential factor for the sustainability of life. Anaerobic organisms can live without oxygen, but they cannot survive without water (Abbasi and Abbasi, 2012). Over human history, water was extensively used in all aspects including drinking, irrigation, energy production, industry, entertainment, etc. Access to freshwater resources that meet the market's demand is considered a great priority for all nations to ensure their food security and socio-economic development. However, the controversial point in this context is the uneven distribution of such fortune in the world. Where the Middle East and North Africa (MENA) region have long suffered from water scarcity due to its arid/semi-arid climate and persistent drought. As an example, Algeria is ranked among the fourteen most water-poor countries on this planet. Numerically, Algeria has a reserve of water estimated at 17 billion shared into surface and groundwater resources with a capacity of 10 billion m^3 and 7 billion m^3 respectively. In 1962, Algeria had an amount of 1500 m^3 of water per inhabitant per year, before falling to 430 m^3 in 2020, which represents a level below the scarcity threshold (1000 m^3) according to the United Nations Development Program and World Bank projections (UNDP, 2009).

Scarcity of water resources in Algeria

Why has Algeria witnessed this dramatic situation of water scarcity?

Indeed, the prevalent situation of limited water quantity has gotten worse when water demand increases, resulting from several synchronized effects such as population growth, improved living conditions, and expansion of agricultural and industrial activities (Bouslah, 2018). Subsequently, the Algerian authorities sought to fill the perceived water deficit by launching a water mobilization strategy. The construction of new dams and reservoirs as well as the implementation of desalination, demineralization, and wastewater treatment systems are the most widely adopted techniques. Nevertheless, the global volume of mobilized water is estimated at only 5 to 6 billion m^3/year, which is regarded as an unsatisfactory amount to guarantee food security for the next generation (Guidoum, 2017). It is axiomatic that the low rate of precipitation in Algeria is one of the many causes of water shortage. This phenomenon is mainly due to the impact of climate change and global warming. In addition to this, three other serious problems have led to a decrease in the storage of dams. The first is the phenomenon of silting, which has deposited 32 million m^3 of sediment per year in 52 large dams. The second is the fact of lake evaporation, which contributed to an average annual water loss of 250 million m^3 in 39 dams, estimated to be about 6.5% of the total capacity. And the third is the leakage of water dams reserve through the banks and foundations, which has reached an average annual loss of 40 million m^3 of water in 22 dams (Remini, 2010).

Water quality degradation and sources of pollution

Why/how is the water quality of Algerian dams assessed?

Based on previous studies conducted on water quality assessment in Algeria, nearly all researchers agree that Algerian dams are influenced by a wide range of natural and anthropogenic pollution, both point and non-point sources. Common sources of non-point pollution can be summarized in sediment transport, weathering processes, agricultural practices, etc. Point source pollution, on the other hand, is represented by domestic wastewater discharges and industrial effluents. In order to secure water that is safe and suitable for multiple daily needs, it is necessary to establish an effective system of sampling sites to track spatial and temporal variations in water quality parameters and pollution indicators. Otherwise, this could have disastrous consequences on human and ecosystem health and may also lead to economic losses. In Algeria, assessment of dams' water quality is carried out by (l'Agence Nationale des Ressources Hydrauliques, ANRH) managers by comparing the physicochemical and bacteriological parameters of a sample with the corresponding guideline values (national standards), before generating detailed reports on the analyzed parameters. This procedure can be effective in identifying factors that are exceeding recommended thresholds and causing contamination, but it is very costly, laborious, and time-consuming and provides little insight into overall water quality status, particularly when many parameters are measured.

Water quality assessment

What approaches/tools are most commonly used?

The need for using sophisticated techniques to facilitate the interpretation of a large amount of generated data on water quality parameters samples is essential today. In the literature, many methods have been adopted and their methodological concepts differ from each other. Some techniques compress and reduce data sets with multiple dimensions and variables to extract a few factors that explain most of the variation in the data, such as multivariate statistical techniques. Collecting water samples from gauging sites for laboratory analyses is not always easily feasible due to the rugged topography. For this reason, the use of remote sensing and geostatistical tools is very necessary and indispensable, for instance, Landsat and Geographic Information System (GIS) versions. Meanwhile, some methods enable to graphically represent the hydrochemical facies of a water sample on specific diagrams. These are commonly used to assess water quality for irrigation purposes, such as Piper, Wilcox, Gibbs, etc. Given the promising results of Multi-criteria Decision-making (MCDM) methods in operational research applications, scientists of water resource management have addressed many problems related to the reliable ranking of water quality sources and assigning weights to parameters involved in developing the water quality index.

What is a Water Quality Index (WQI)?

WQI is simply a mathematical approach that expresses the overall water quality status of a sample in a single explanatory value obtained by integrating complex data sets of water quality parameters (Khan et al., 2003). Moreover, WQI can be used for multiple benefits, such as helping managers in (i) allocating funds and identifying priorities (water treatment), (ii) comparing and ranking water quality of different sources and locations, (iii) determining the extent of exceeded standards by studied sites, (iv) figuring out the changes of water quality over a certain period (deterioration or improvement) and (v) keeping the public informed in water quality of a source in easily way (score). It was initially proposed by Horton (1965), since then, various indices have been formulated and developed by many researchers and institutions such as the US National Sanitation Foundation's Water Quality Index (NSF-WQI) (Brown et al., 1970), Canadian Council of Ministers of the Environment's WQI (CCME WQI). In fact, these conventional WQIs have been subjected to literary criticism either for failing to consider sufficient numbers of selection parameters or for choosing an arbitrary number of variables based on experts' opinions. Besides, assigning weights subjectively to parameters from the judgment of subject specialists and policy-makers using rating curves, and deterministic equations. But with time and in light of technological development, several researchers have used advanced statistical methods and artificial intelligence to overcome the aforementioned drawbacks and develop robust indices, relying mainly on natural language reasoning and objective bias in information processing. Such approaches have yielded promising results, as with those who have employed information entropy (Amiri et al., 2014; Li et al., 2010; Ukah et al., 2020), fuzzy logic (Icaga, 2007; Lermontov et al., 2009; Ocampo-Duque et al., 2006), genetic algorithm (Peng, 2004), stochastic (Beamonte et al., 2005), and self-organizing map (SOM) (Lu and Lo, 2002) methods, etc.

Since there are a large number of studies in the literature assessing the water quality of abroad dams using WQI, such as Samiotis et al., (2018) from Greece, applied the modified NSF-WQI to compare the water quality of two in-line reservoirs namely Polyfytos and Ilarion. The results revealed that the transformation of the Aliakmon River into the young Ilarion Reservoir has affected the water quality and is characterized by a lower quality than the Polyfytos dam. Farzadkia et al., (2015) found that the main sources of pollution in the Yamchi dam basin using the Canadian WQI are wastewater discharges from such recreation centers, also, the water quality for drinking water use is described as poor but for irrigation is classified as excellent to fair.

To the best of our knowledge from a national perspective, research on using WQI for assessing dams' water quality in Algeria is still limited. A few extant studies have been conducted for individual reservoirs such as Bouguerne *et al.,* (2017) employed PCA/FA, CA, and DA to assess the temporal variations of water quality at Ain Zada dam for 10 years. As such, PCA and FA methods revealed that the parameters responsible for water quality variations were mainly related to salinization factor and organic pollution. The water quality of Ain Zada dam has been classified as medium to good by using NSF-WQI. Bouslah et al., (2017) study aimed to evaluate the water quality of Koudiet Medouar dam for its suitability for potability using WQI based on the weighted arithmetic method. Due to the high contamination in such a dam, the water is unfit for human consumption without prior treatment. Or specific regions like (Hamlat et al., 2016; Hamlat et al., 2013), but none has been explicitly dedicated to the whole northern part.

Contributions

The main objective of this thesis is to evaluate the surface water quality of a large number of Algerian dams. The present contribution has been divided into two-fold. The first study is devoted to assessing the water quality of forty-seven (47) dams using our newly developed Water Quality Index based on the Data Envelopment Analysis (DEA-WQI) approach. Among all the selected dams, Beni Haroun (BH) dam has been selected separately as a specific case in the second part of our contribution, given its major importance in the country. Under the same framework of an integrated approach, several methods were employed, including CCME-WQI, Principal Component Analysis and Factor Analysis (PCA/FA), K-means clustering, and Ordinary Least Squares (OLS) to perform a comprehensive assessment of the water quality of BH dam and its upstream “Wadi Rhumel”.

This work will be particularly useful to water resources managers as decision supports towards:

- *Create nationally an effective water quality benchmarking system by assigning a proper WQI to each dam.*
- *Use a new index to determine spatial-temporal variations and trends in water quality for any kind of water body (groundwater or surface water).*
- *Identification of latent sources of water quality deterioration.*
- *Estimation of the costs of water treatment processes.*
- *Allocating funds to the water treatment plants in sites and regions that are most affected by polluting resources.*
- *Prioritization of the most critically affected areas.*

Thesis Organization

The present thesis is structured in 3 parts:

Part I: A literature review

It encompasses two separate chapters, the first one presents the existing surface water resources in Algeria and the different kinds of pollution factors that contributed to the deteriorating quality, then, the state of the art chapter describes the most commonly adopted techniques for water quality assessment and focuses pretty more on development of WQI tool.

Part II: Material and methods

This part is dedicated to an overall description of the study area of the selected dams in terms of geographic, topographic, and climatic context, as well as to recalling the adopted ANRH measures for water quality assessment in Chapter (iii). On the other hand, chapter (iv) gives the different definitions of used approaches. Where the proposed methodology for developing a new WQI based on DEA model has been described herein detail.

Part III: Results and discussion

The last part presents the outcome of our research which is translated into two contributions. Chapter (v) aims to evaluate the water quality of 47 Algerian dams defined by 10 hydrochemical parameters over 11 months via DEA-WQI application, while chapter (vi) examines the water quality of Beni Haroun dam along with its upstream for long-term evaluation (11 years) using a combination of different techniques within the same methodological framework.

Part I

Literature Review

Chapter I:

Surface water resources in Algeria and pollution's problem

Introduction

Water is a precious wealth nowadays, especially for the nations that enjoy arid and semi-arid climates and suffering from severe scarcity of water resources, as with Algeria. It is ranked among the fourteen most water-poor countries on the planet. Moreover, an increasing rate of population growth (about 45 million inhabitants by 2020) and industrialization activities have led to a further complication in water sustainability.

Mismanagement of water resources was also highlighted as another factor contributing to worsening the current problem. Accordingly, the Algerian authorities have adopted an ambitious plan to valorize surface water through the construction of new dams and reservoirs and mobilizing non-conventional water resources by implementing desalination, demineralization, and wastewater treatment techniques to make up the perceived water deficit.

To make the situation worse, one more problem no less important than water scarcity emerged, which is water quality degradation. As a result, identifying factors that are responsible for water pollution has become an imperative measure as before. Both point and non-point sources of pollution have been characterized as the main causes of water contamination. This chapter presents an overview of the existing water resources in Algeria, the types of water pollution, as well as the definitions of certain water quality parameters and their standards, for different uses both locally and internationally.

I.1. Conventional water resources in Algeria

Paradoxically, Algeria stretches on the largest area in the African continent, but it has solely an amount of water estimated at 17 billion m^3 compared to other countries because according to recent research, the Middle East and North Africa (MENA) region has been regarded as the most vulnerable area to the risk of climate change. The global water reserve in Algeria is divided between surface and groundwater resources with a capacity of 10 billion m^3 and 7 billion m^3 respectively.

The "*Albian*" reserve in the deep aquifers of the Sahara basin represents the largest partition of groundwater volume with an estimated amount of 5 billion m^3, of which approximately 32% of this volume has been used (ADE 2011). The latter capacity is considered as a non-renewable water table, so that the opportunities for its extensive exploitation are quite limited, whether for ensuring the proportion of future generations or to respect the agreement outlined with neighboring countries that share the resource of the fortune, including Tunisia and Libya. Furthermore, the big number of wells and springs in the country is subjected to an increasing level of pumping, where 90% of the aquifers are exploited (Drought management strategy in Algeria, 2014).

Figure I.1. The 05 principal Algerian watersheds (Drouiche et al., 2012)

Otherwise, surface water resources are exclusively concentrated in the northern part of Algeria due to the uneven distribution of rainfall. In which, the precipitation rate proportionally declines towards the southern zone with an annual rainfall record of less than 89 mm in the Sahara watershed (ABHS 2005). Detailed metrics of conventional water resources, i.e. surface water and groundwater, are shown in Table I.1 for each principal watershed (see Figure I.1).

Table I.1. Conventional water resources in Algeria (Hamiche et al., 2015)

Basin	Surface water (Hm^3)	Groundwater (Hm^3)	**Total**
Oranie-Chott Chergui	650	600	**1250**
Cheliff-Zahrez	1710	830	**2540**

Algérois-Hodna-Soummam	1690	740	**2430**
Constantinois-Seybouse-Mellegue	3000	430	**3430**
Sahara	370	5000	**5370**
Total	**7420**	**7600**	**15020**

I.1.1. Surface water resources

In addition to the existence of rivers, lakes, and wetlands in Algeria, dams and artificial reservoirs are considered the main surface water resource in the country. The great importance of these infrastructures resides mainly in fulfilling the most vital aspects of humankind's requirements such as water supply, irrigation, flood control, power generation, and other purposes.

I.1.2. Dams' water

Since the 1990s, Algeria has launched an ambitious policy of building new dams that secure the national market's demand and cover the perceived deficit of water availability. However, this strategy has ensured around 17% of annual needs (Drouiche et al., 2012).

Such dams and reservoirs have known five separate periods of construction and restoration, starting from the colonial period (before 1962) when only thirteen dams have been built to store 450 million m^3 of water intended mainly for the irrigation of the agricultural plains of the western part until nowadays with an approximately stored reserve of 8.4 billion m^3 in 84 constructed dams (MRE ,2016). Table I.2. provides some characteristics for each observed dam.

Table I.2. List of the main existing dams

N°	Name	Wadi	Operating Year	Capacity (Hm^3)(a)	Volume (Hm^3)(b)	Purpose
01	Fergoug,	El Hammam	1970	1.0300	0.840	WS, IRR, IND
02	Bouhanifia,	El Hammam	1948	34.520	15.792	WS, IRR
03	Sidi M'hemed Ben Aouda,	Mina	1970	153.710	43.322	WS, IRR
04	Merdja Sidi Abed,	Cheliff	1984	47.970	NA	WS, IRR
05	Oiuzert,	Taria	1986	93.910	26.474	TRANS
06	Gargar,	Rhiou	1988	358.280	328.531	WS, IRR
07	Cheurfa,	Mebtouh	1992	70.210	27.516	WS, IRR
08	Boughrara,	Tafna	1999	175.450	139.165	WS, IRR
09	Beni Bahdel,	Tafna	1946	54.630	15.519	WS, IRR

10	Mefrouch,	Mefrouch	1963	14.990	2.564	WS, IRR
11	Sidi Abdelli,	Isser	1988	106.610	57.239	WS
12	Bakhadda,	Mina	1936	39.940	35.993	WS
13	Sarno,	Sarno	1954	21.250	11.146	WS
14	Dzioua,	Tafna	1988	13.000	4.840	WS
15	Sikkak,	Sikkak	2004	25.500	25.470	WS
16	Kramis,	Kramis	2004	45.380	13.384	WS, IRR
17	Dahmouni,	Nahr Oussel	1987	39.520	24.506	WS, IRR
18	Cheliff (MAO),	Cheliff	2009	50.000	50.000	WS
19	Kerrada,	Cheliff	2009	65.000	58.690	WS
20	Bougara,	Nahr Oussel	1989	11.320	10.820	IRR
21	Koudiet Rosfa,	Fodda	2004	75.000	69.528	WS
22	Tichy Haf,	Boussalem	2007	81.800	55.972	WS, IRR
23	Hamiz,	Arbatache	1894	15.530	8.981	TRANS, IRR
24	Beni Amrane,	Isser	1988	11.850	7.538	TRANS
25	Keddara,	Boudouaou	1985	142.390	82.621	WS
26	Ghrib,	Chellif	1939	116.320	111.408	WS, IRR
27	Bouroumi,	Bouroumi	1985	181.860	81.793	WS, IRR
28	Boukourdane,	El Hachem	1992	105.000	38.559	WS, IRR
29	Deurdeur,	Tighzir	1984	105.120	57.131	WS, IRR
30	Lekhal,	Lekhal	1985	27.16	15.135	WS, IRR
31	Harreza,	Harreza	1984	76.650	8.372	IRR
32	Fodda,	Fodda	1932	102.850	84.668	IRR
33	Sidi Yakoub,	Ardjen	1985	252.850	231.539	WS, IRR
34	Oued Mellouk,	Rouina	2003	119.400	31.884	IRR
35	Taksebt,	Aissi	2001	181.020	144.882	WS, IRR, TRANS
36	Tilesdit,	Dous	2004	164.55	156.440	WS
37	Sidi M'hemed Ben Taiba,	Chellif	2006	75.000	63.967	WS
38	Meurad,	Djebroune	1860	0.200	0.158	IRR
39	Ladrat,	Ladrat	1989	8.470	6.854	IRR
40	Koudiet Acerdoune,	Isser	2009	640.000	334.112	WS, IRR, TRANS
41	Boughezoul,	Nahr Oussel	1934	20.270	13.696	TRANS
42	Tigzel,	Tigzel	2019	2.045	NA	WS
43	Ain Zada,	Bousselam	1986	121.400	27.810	WS
44	Hammam Grouz,	Rhumel	1987	40.150	8.462	WS
45	Zardezas,	Saf-Saf	1947	16.860	10.703	WS, IRR, IND
46	Guenitra,	Fessa	1984	117.820	68.689	WS, IRR, IND
47	K'sob,	K'sob	1940	30.00	22.720	IRR
48	Ain Dalia,	Medjerda	1987	76.080	35.877	WS
49	Cheffia,	Bounamoussa	1965	158.830	107.933	WS, IRR, IND
50	Hammam Debagh,	Bouhamdane	1987	184.350	106.651	WS, IRR
51	Mexa,	Kebir-Est	1999	30.270	29.581	WS
52	El Agrem,	El Agrem	2002	33.040	32.783	WS

53	Beni Zid,	Beni Zid	1993	39.390	39.855	WS, IRR
54	Ighil Emda,	Agrioun	1953	160.000	154.000	WS, IRR
55	Zit Emba,	El Hammam	2001	116.590	97.915	WS, IRR
56	Koudiet M'douar,	Chemora	2003	74.320	43.009	WS, IRR
57	Beni Haroun,	Rhumel	2003	960.000	996.937	WS, IRR, TRANS
58	Oued Athmania,	El Kaim	2007	33.000	30.269	WS, IRR
59	Kissir,	Kissir	2010	68.000	66.530	WS, IRR
60	Babar,	Babar	1995	38.010	34.834	IRR
61	Boussiaba,	Boussiaba	2010	120.000	119.458	WS
62	Foum El Gueiss,	Gueiss	1939	0.430	0.430	WS, IRR
63	Foum El Khanga,	Cherf	1995	152.650	50.731	IRR
64	Fontaine des Gazelles,	El Hai	2000	54.740	30.721	IRR
65	Foum El Gherza,	El Abiod	1950	14.89	11.118	IRR
66	Djorf-Torba,	Guir	1969	260.25	168.98	WS, IRR
67	Brezina,	Mouilah	2000	108.47	94.34	IRR
68	Cheurfa II,	Mebtouh	1992	70.21	42.39	IRR
69	Sfsaf,	Safsaf	2010	20.00	NA	WS
70	Kef Eddir,	Damous	2015	125.000	69.60	WS, IRR
71	Draa Diss,	Medjaz	2015	189.60	151.00	WS, IRR
72	Douera,	O. Ben Amar	2015	87.000	NA	WS, IRR
73	Tabellout,	Djendjen	2018	294.40	189.00	WS, IRR
74	Ourkiss,	Ourkiss	2018	64.00	24.120	WS, IRR
75	Tagharist,	Tagharist	2018	5.700	NA	WS, IRR
76	Ouldjet Mellegue,	O. Mellegue	2020	156.00	136.00	WS, IRR
77	Mahouane,	El Guessar	2015	119.00	NA	WS, IRR
78	Erraguen,	Djendjen	1962	220.00	110.00	IRR
79	Bougous,	Bougous	2010	66.000	59.764	WS, IRR

(a) Estimated capacity; (b) Average volume; NA: Not Available; WS: Water supply; IRR: Irrigation; IND: Industry; TRANS: Transfer.

I.1.3. The strategy of water mobilization and transfer

Due to climate change vulnerability and persistent drought, Algeria has experienced severe consequences in water resource scarcity. Where the quantity of its water reserve has been observed among the lowest worldwide thresholds compared to the United Nations Development Program (UNDP) and World Bank. Moreover, the uneven distribution of water resources between the different regions of the Algerian territory has raised another issue of water management tasks.

In order to compensate for geographical disparities, a regional transfer program aimed at ensuring greater equity between territories in terms of access to water has been gradually implemented. These water transfers also meet the objectives of the country's food security strategy, which aims to support regions with strong agricultural potential (MRE ,2016). The major Algerian projects of dams' water transfer are represented in detail in Table I.3.

Table I.3. Mega-projects of dams' water transfer (MRE ,2016)

Transfer system	Destination (Cities)	Capacity (hm^3/year)	Population (M inhab)
Beni Haroun	Constantine; Mila; Jijel; Batna; Oum El Bouaghi; Khenchela	504	4
Koudiat Acerdoune-high plateaus system	Bouira; Médéa; Tizi Ouzou; M'sila	178	2
Tichy Haf-Béjaia transfer	Béjaia	150	1.5
Taksebt	Algiers; Tizi Ouzou	180	5
Mostaganem-Arzew-Oran (MAO)	Mostaganem; Oran	155	1.5
Setif-Hodna-El Eulma transfer	*Eastern Corridor*: El Eulma	191	0.75
	Western Corridor: Setif	122	1.107

I.2. Non-conventional water resources in Algeria

Non-conventional water resources have become a major priority for the Ministry of Water Resources to address regional conventional water deficits and to ensure future security in the mobilization of water resources. They involve the production of freshwater through the desalination of seawater or demineralization of brackish water, and the reuse of wastewater.

I.2.1. Desalination

Seawater desalination may be the most appropriate solution to the situation in Algeria because it not only secures the drinking water supply of coastal cities and meets industrial needs, but also frees up large quantities of water from dams for irrigation. The desalination system comprises 13 stations with a capacity of 2.31 million m^3/d, including 11 operating stations with a capacity of 2.1 m^3/d serving about 8,232,305 inhabitants as shown in Table I.4.

Table I.4. Stations of seawater desalination

Region	Station	Capacity (m3/day)	Operating year
West	Arzew (Oran)	86×10^3	2006
	Souk Tleta (Telemcen)	200×10^3	2011
	Honaine (Tlemcen)	200×10^3	2012
	Mostaganem	200×10^3	2011
	Sidi Djelloul (Ain Timouchent)	200×10^3	2010
	Mactaa (Oran)	500×10^3	2015
Center	Hamma (Algiers)	200×10^3	2008
	Cap Djinet (Boumerdes)	100×10^3	2014
	Fouka (Tipaza)	120×10^3	2011
	Oued Sebt (Tipaza)	100×10^3	/
	Tenes (Chlef)	200×10^3	2015
East	E'chatt (Taref)	100×10^3	/
	Skikda	100×10^3	2009

I.2.2. Demineralization of brackish water

Brackish water accounts for about a quarter of the national groundwater, mainly located in the desert and semi-desert regions of Algeria. Brackish water production was started in 2000. The mobilized amount is estimated at 510,160 hm^3/year of which 160 hm^3/year is used to satisfy the water supply sector. Twelve (12) stations are in operation in the provinces of Tlemcen, Oran, Tizi-Ouzou, Bejaia, Illizi, Biskra, Ouargla, Médéa, and Ain Defla. Drinking water production is approximately 24.2 hm^3/year.

I.2.3. Re-use of treated wastewater

Under the umbrella of MRE, the National Office of Sanitation (L'office National d'Assinissement, ONA) is responsible for managing approximately (271) wastewater treatment plants (in operation and under construction) across the country to produce a nominal volume of treated wastewater estimated at 800 hm^3/year using activated sludge and lagooning processes. The resulting water is used primarily to satisfy irrigation water demand as well as other non-potable uses (municipal and industrial).

I.3. Water pollution

Water pollution is any change in physical, chemical, or biological properties, or any release of liquid, gaseous or solid substances into the water that makes it unsafe and harmful to public health or to agricultural, industrial, and other activities, or to wildlife and aquatic life, as it is defined by WHO (Guerraiche, 2017).

In the last few years, water pollution has become the most human concern in the light of acute demographic growth and remarkable expansion of agricultural and industrial activities. Besides, most researchers in the literature are agreed that the origins of water pollution can be classified into two types viz. point and non-point source pollution.

I.3.1. Non-point source pollution

Such pollution, by definition, comes from multiple sources, which are often difficult to identify. Among the well-known non-point sources of pollution, agricultural practices, are generally considered to be the main contributor of pollutants that can threaten surface water due to the runoff mechanism as well as groundwater through the infiltration of nutrients into deep aquifers. The main causes of diffuse surface water pollution can be summarized in the following bullets:

I.3.1.1. Erosion and sediment transport

Sediment transport is a natural process that occurs when the amount of solid materials is moved from one site to another via different factors such as air, water, or gravity forces. Usually, soil weathering is the key factor that triggers sediment transport. In Algeria, farmlands are considered a major source of non-point source pollution by which agricultural practices remove a significant part of the plant cover, putting the soil surface at risk of water or wind erosion. The weathered soil is then transformed into deposit sediment, leading to potential water pollution (Gaagai, 2017).

Interestingly, recent studies related to the problem of silting have shown that the annual volume of sediments deposited behind Algerian dams is estimated at 45 million m^3, hence reducing the storage capacity of dams (Remini and Hallouche, 2007).

I.3.1.2. Agricultural fertilization

It is noteworthy that fertilization activities have played a key role in increasing crop yields and agricultural development. However, excessive and non-rational nutrient inputs to farmland allow nearby rivers and lakes to become contaminated by nitrogen and phosphorus leaching from their banks. As a result, it causes algal blooms and eutrophication problems.

I.3.1.3. Pesticides

Insecticides, herbicides, or fungicides all are chemical substances commonly used to protect crops from potentially harmful pests and parasites. They generally have a negative impact on aquatic life (fish and living organisms) if they migrate to surface waters. Furthermore, neighboring livestock are also vulnerable to the risk of water-borne diseases after consumption which leads to animal and economic losses.

I.3.2. Point source pollution

Unlike the former type, this source of pollution is basically linked to a single input of pollution strongly produced by anthropogenic activities, which comes mainly from domestic wastewater discharges and industrial effluents.

I.3.2.1 Domestic pollution

In most urban and municipal areas, wastewaters are collected in the sewer system and then transported by gravity through the main pipeline to the Wastewater Treatment Plant (WWTP) to provide the agricultural sector with cleaner water. However, this operation is often not available in areas located outside of large provinces and crowded cities where there are no treatment plants. In such cases, household discharges, waste oil, feces, spills from slaughterhouses, and detergents are frequently dumped into receiving streams (rivers), which make the surface waters to be polluted and contaminated.

I.3.2.2 Industrial pollution

Given the serious impact of industrial effluents on the environment and aquatic life, the implementation of monitoring systems at plants' outlets is considered a top priority to mitigate the expected losses. In addition to the organic pollutants that characterize domestic discharges, industrial pollution contains several types of pollutants and toxic elements such as remains of paper mills, heavy metals, dyes, tanneries, textiles, etc (Kenneth and William, 2012).

I.4. Water quality parameters

I.4.1. Physical indicators

I.4.1.1. Temperature

Water temperature is considered one of the most important factors of water quality in the aquatic life system. Because it has a significant interdependence with other factors, like dissolved gases (ex., Dissolved oxygen) and water viscosity. Yet, reproduction, growth, and metabolic rates of organisms depend upon the temperature (Hauer and Lamberti, 2011). Temperature changes are related to air temperature, rainfall-runoff, groundwater inflow, and sun exposure, and vary throughout the day, season, and year (Gaujou, 1995).

I.4.1.2. Dissolved Oxygen (DO)

The existence of lower concentrations of dissolved oxygen (DO) in water can cause an imbalance in the biological activities of aquatic life and could even lead to the death of fauna and flora organisms including fish and plants. The concentration of dissolved oxygen is controlled by several variable physical and biological processes such as temperature, photosynthetic processes, aquatic plant respiration, and breakdown of organic matter by microorganisms (Cox, 2003).

I.4.1.3. Electrical conductivity (EC)

The conductivity factor refers to the amount of dissolved inorganic substances (electrolytes) in water. The more mineralized water, the higher the electrical conductivity. Water mineralization is dominated by major ions, such as calcium, magnesium, sodium, potassium, chlorides, sulfates, nitrates, etc (Gaagai, 2017). The unit of measurement of EC is Micro-siemens per centimeter (μS/cm).

I.4.1.4. pH

pH is a measure of the hydrogen atom (H^+) that indicates the acidity or alkalinity of the water. Water will be alkaline if the concentration of (OH^-) is higher than (H^+) i.e., $pH > 7$. Otherwise, water will be acidic i.e., $pH < 7$.

I.4.1.5. Turbidity

The suspended and undissolved particles represent the turbidity of water. This latter can be found in organic and inorganic particles enclosing sands, clays, microbes, and phytoplankton. Typically, turbidity is defined by the degree of light reflected by these particles.

I.4.1.6. Total solids

Total Solids (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).

I.4.2. Chemical indicators

I.4.2.1. Major ions

I.4.2.1.1. Calcium

Calcium (Ca^{2+}) is a divalent cation with an atomic weight of 40. it is found in calcareous rocks in the form of carbonate or calcium silicate. This is one of the six main elements. It is a material essential to the structure of living beings, present in teeth, bones, shells, leaves, and cell walls (FAO ,2002).

I.4.2.1.2. Magnesium

Magnesium (Mg^{2+}) is a common element on our planet, generally a slow-reacting element, notably in its dissolution, however, its reactivity increases with the level of oxygen. Together with calcium, it is one of the main constituents of hardness.

I.4.2.1.3. Sodium

Sodium (Na^{+}) is a ubiquitous ion found in all water types due to its high solubility. It comes from the leaching of ($NaCl$) compound, from clay and clay-marl formations, and from domestic wastewater discharges (WHO ,2008).

I.4.2.1.4. Potassium

Potassium (K^{+}) is a highly reactive mineral, present in various forms, whose extraction is done through weathering processes from silicates, sylvite, potassium clays, chlorinated minerals, and the dissolution of chemical fertilizers (NPK).

I.4.2.1.5. Chloride

Chlorides (Cl^-) exist naturally as components of salt ($NaCl$) and magnesium chloride ($MgCl_2$) or, in some cases, in combination with potassium or calcium. Chloride is often used as a disinfecting in treatment plants and as a bleaching agent in industrial applications. The levels of chloride in groundwater are rather low compared to surface water. Sufficient quantities of chlorides ensure normal cell functions in plants and animals (WHO ,2008).

I.4.2.1.6. Sulfates

Sulfate (SO_4^{2-}) ions are extremely soluble and can be present in many minerals, including barite ($BaSO_4$), epsomite ($MgSO_4$-$7H_2O$), and gypsum ($CaSO_4$-$2H_2O$). Industrial discharges such as pulp mills, tanneries, and textile mills are also the main sources of sulfates.

I.4.2.1.7. Bicarbonate

In almost all mineral waters, which come from limestone-rich regions, the bicarbonate (HCO_3^-) content is generally high. It is considered the main alkaline factor and an important opponent of acids. It acts as an acid buffer, giving mineral water a natural and pleasantly neutral taste (Gaagai, 2017).

I.4.2.2. Nutrients

I.4.2.2.1. Nitrate

The most common source of nitrogen in surface waters is nitrate (NO_3^-), which forms naturally when nitrogen combines with oxygen or ozone. NO_3^- is the stable form of combined nitrogen for oxygen systems. Excess levels of NO_3^- in drinking water can be hazardous to the health of pregnant women and infants causing Methemoglobinemia disease. This compound is found in the soil or comes from chemical industrial pollution, waste dumps, or nitrogen fertilizers (Patroncini, 2013).

I.4.2.2.2. Nitrite

In contrast to nitrate, nitrite (NO_2^-) is a less stable form because under aerobic conditions Ammonium can be oxidized by nitrifying bacteria to NO_2^- and then to NO_3^-. Nitrite is produced from fertilizers by runoff, wastewater, and various mineral deposits.

I.4.2.2.3. Ammonium

Ammonium (NH_4^+) is the most toxic form of nitrogen. It has long been used in water treatment plants to extend the effectiveness of disinfectant chlorine added to drinking water. Its presence in water is linked to a natural or anthropogenic origin, i.e. plants and animal remains or urban and industrial discharges (WHO ,2008).

I.4.2.2.4. Phosphate

Phosphate (PO_4^{3-}) is a chemical compound containing phosphorus. This latter is indispensable to life and is found as inorganic phosphates in the rock. PO_4^{3-} affects water quality by causing excessive algae growth and reducing oxygen in the water. The eutrophication phenomenon can lead to fish mortality and habitat loss with the disappearance of various species (Rail, 1989).

I.4.2.3. Organic-chemical parameters

I.4.2.3.1. Biochemical oxygen demand

Biological oxygen demand (BOD) is defined as the amount of dissolved oxygen required by aerobic microorganisms to breakdown organic matters (biodegradable) under specified conditions (at 20°C and in the dark for 5 days). It is expressed in mg O_2/L (Chapman, 1996).

I.4.2.3.2. Chemical oxygen demand

Chemical oxygen demand (COD) represents the equivalent amount of oxygen needed to chemically oxidize organic compounds and oxidizable mineral salts (e.g. ammonia and nitrites) in water. The COD/BOD ratio indicates the nature of the existing pollution in the water and whether the pollutants are more, less, or not at all biodegradable.

I.4.2.3.3. Organic matter

Organic matter (OM) is a carbon-based compound that comes mainly from the residuals of plant and bacterial degradation. OM is present in both surface and groundwater but has no direct impact on human health, it affects the efficiency of drinking water treatment processes and therefore the safety of drinking water (CCME, 2001).

I.4.2.4. Heavy metals

I.4.2.4.1. Copper

Copper (Cu^{2+}) is found in many kinds of water, but it is mostly present in complexes or the form of particles. This trace element is necessary for human health. But, copper production is increasing and spreading remarkably in the environment through mining, metal production, fertilizer production, and animal feed. Chronic copper poisoning leads to Wilson's disease and causes nausea, vomiting, diarrhea, gastric complaints, and headaches (WHO ,2008).

I.4.2.4.2. Zinc

Zinc (Zn^{2+}) is generally present in the form of sulfide ores, such as sphalerite (ZnS) and smithsonite ($ZnCO_3$). The solubility of zinc in water depends mainly on pH and temperature factors; the more acidic the environment, the greater the solubility. Exposure to 2 g of zinc sulfate at one time will cause acute toxicity resulting in stomach upset and vomiting.

I.4.2.4.3. Iron

Iron (Fe^{2+}) can be dissolved in water as ferrous iron. Once this water is exposed to air, it becomes cloudy and a reddish-brown precipitate of insoluble ferric iron occurs. Iron is a crucial trace element for maintaining energy metabolism and preventing iron deficiency anemia. When high levels of iron are absorbed, severe damage to vital organs of the pancreas, liver, spleen, and heart can occur in patients with hemochromatosis (Wang, 2016).

I.4.2.4.4. Manganese

Manganese (Mn^{2+}) is the most abundant metal and is present in surface and groundwater sources. Human activities are responsible for much of the manganese contamination of water. Hallucinations, memory loss, and nerve damage are some of the symptoms of manganese poisoning. Also, manganese can cause Parkinson's disease, pulmonary embolism, and bronchitis (Lenntech, 2020).

I.5. National and international standards

Water quality standards, regulations, or guidelines, all these concepts can be defined as desired concentrations of physicochemical and biological parameters that make water quality suitable for a specific use.

Water Quality Standards (WQS) is not a recent term, as it dates back to the 19th century, in 1832, when cholera claimed the lives of many people in London (UK) because they used the Thames for drinking. Surprisingly, however, the onset of the disease was attributed to an atmospheric miasma rising above the Thames rather than to the water itself, since at that time there were virtually no analytical methods available to identify the origin of the contamination (Scholz, 2016). Until Doctor Snow discovered that the discharge of human sewage from wealthier households into the Thames was the main cause of cholera infection, mapping the areas where the disease was spreading and interviewing those infected (National Research Council, 1999).

Since then, worldwide organizations have established a series of laws and guidelines on water quality standards to protect public health and aquatic life from contamination and potential diseases.

I.5.1. Algerian laws

Based on the provision law of the Official Journal of the Algerian Republic (OJAR, 2011) n° 05-12 of 28 *Joumada Ethania* 1426 corresponding to August 4, 2005, modified and completed, relating to water, of the executive decree n° 11-219 of 10 Rajab 1432 corresponding to June 12, 2011, fixing the quality objectives of surface and groundwater intended for water supply. Articles relating to such decrees have been pointed out as follows:

Article 1. - Under the provisions of article 50 of the law n° 05-12 of 28 *Joumada Ethania* 1426 corresponding to August 4, 2005, modified and supplemented, above-mentioned, the present decree aims at fixing the quality objectives whose quality must be met by groundwater as well as surface water flows and reservoirs intended for the water supply of the populations.

Article 3. - Quality objectives provided in Article 1 above correspond to the maximum values set for organoleptic, physicochemical, chemical, and microbiological parameters (see Table I.5).

Table I.5. Algerian standards of surface-water quality parameters

Parameters	Unit	Threshold values
Color	Mg/L (Pt/Co scale)	200
Odor (at 25°C)	-	20
Temperature	°C	25
Cl^-	Mg/L	600
pH	-	≥ 6.5 & ≤ 9
EC	µS/cm	2800
Suspended Solids (SS)	mg/L	25
SO_4^{2-}	mg/L	400
DO	% O_2	30
NH_4^+	mg/L	4
NO_3^-	mg/L	50
PO_4^{2-}	mg/L	10
Kjeldahl Nitrogen	mg/L	3
BOD_5	mg/L (O_2)	7
COD	mg/L (O_2)	30
Cu^{2+}	mg/L	2
Fe^{2+}	mg/L	1
Mn^{2+}	mg/L	1
Zn^{2+}	mg/L	5
Arsenic (As)	µg/L	100
Lead (Pb)	µg/L	50
Mercury (Hg)	µg/L	10
Escherichia coli	n/100ml	20,000
Enterococcus	n/100ml	10,000

Article 4. - The control of compliance with the maximum values is carried out by the water resources administration at the level of the following works and installations for the water mobilization:

- Wells, springs and other groundwater catchment works.
- Surface flow diversion works (transfer projects).
- Surface water reservoirs (dams).

Article 7. - Once the threshold values of some or all parameters have been exceeded, authorities responsible for water resources must notify the relevant organizations to take appropriate measures to ensure the water supply sustainability to inhabitants without any health risk.

The methods of application of this article shall be determined by order of the minister responsible for water resources.

I.5.2. International standards

World Health Organization (WHO, 2008) standards are among the worldwide adopted guidelines for drinking water quality. At the same time, Food and Agriculture Organization (FAO, 1994) has also developed guidelines recommended for irrigation purposes. For objectives related to industrial and aquatic life, we have selected several sources of water quality standards, such as the Canadian Council of Ministers of the Environment (CCME, 2001), the Department of Water Affairs and Forestry (DWAF, 1996), and the Commission of European Committees (CEC, 1978).

Table I.6. International standards of water quality parameters

Parameters	**Unit**	**WQS**			
		Drinking	**Irrigation**	**Industry**	**Aquatic life**
pH	—	≥ 6.5 & ≤ 9[a]	≥ 6.5 & ≤ 8.4[a]	≥ 5 & ≤ 9[c]	≥ 5 & ≤ 9[c]
DO	% O_2	≥ 50[a]	NA	NA	NA
EC	µS/cm	≤ 400[a]	≤ 700[b]	NA	NA
Suspended Solids (SS)	mg/L	NA	2000[b]	NA	NA
Ca^{2+}	mg/L	< 100[a]	< 1600[b]	NA	NA
Mg^{2+}	mg/L	< 30[a]	< 10[b]	NA	NA
Na^+	mg/L	< 200[a]	< 70[b]	NA	NA
K^+	mg/L	NA	2[b]	NA	NA
Cl^-	Mg/L	< 250[a]	< 250[c]	< 150[c]	< 250[c]
SO_4^{2-}	mg/L	< 250[a]	NA	< 200[c]	< 500[c]
HCO_3^-	mg/L	NA	≥ 90 & ≤ 500[b]	NA	NA
NO_3^-	mg/L	< 50[a]	< 10[c]	NA	NA
NO_2^-	mg/L	< 0.1[a]	NA	NA	NA
NH_4^+	mg/L	< 0.5[a]	NA	NA	< 1.37[c]
PO_4^{2-}	mg/L	< 10[a]	< 2[b]	NA	NA
COD	mg/L (O_2)	< 30[a]	NA	< 50[d]	NA
BOD	mg/L (O_2)	< 7[a]	NA	NA	NA

Cu^{2+}	mg/L	< 0.01[a]	< 1[c]	NA	< 1[c]
Zn^{2+}	mg/L	< 0.02[a]	< 5[c]	NA	< 5[c]
Fe^{2+}	mg/L	< 0.172[a]	< 5[b]	< 10[d]	NA
Mn^{2+}	mg/L	NA	NA	< 10[d]	NA

[a]WHO; [b]FAO; [c]CCME; [d]DWAF; [e]CEC and NA: not available.

Conclusion

In spite of the strategic area that Algeria occupies, the scarcity of water resources is considered a major issue that burdens decision-makers. In 1962, Algeria had 1500 m^3 of water per inhabitant per year, before falling to 430 m^3 in 2020 according to UN projections due to the impact of the climate change phenomenon. Furthermore, the acceleration of population growth and the rapid expansion of land use for agricultural and industrial development have led to the deteriorating quality of the remaining surface and groundwater. From the latter, the need to sound the alarm and seek effective solutions to remedy this dramatic situation has been a top priority.

As a result, authorities in charge of water resources management have adopted ambitious plans to mobilize surface water through the construction of new dams in terms of conventional resources and the exploitation of non-conventional resources by implementing desalination and demineralization techniques for water supply needs as well as the treatment of domestic wastewater, which is mainly dedicated to the irrigation of agricultural land. Nevertheless, setting up multiple stations of water quality monitoring in sensitive locations remains an unavoidable action to observe the potential factors responsible for variations in quality parameters.

Finally, getting better knowledge on the existing water resources in Algeria and the risks that threaten its sustainability or its quality will be a good support for better interpretation of the results to be obtained afterward.

Chapter II:

Water quality assessment: state of the art

Introduction

Throughout human history, the existence of water has played an essential role in the development of ancient civilizations. In the 20th century, the main concern of the world nations was to obtain sufficient water to meet the market's demand. But until recent decades, the need to interest water quality has been strongly required due to the increased pollution threatening the environmental system. Thus, water quality has gained too much value relative to water quantity.

In the past, determining adequate water quality for human needs (e.g., drinking), is only confined to consider some common factors relating to organoleptic properties like odor, color, taste, etc. Afterward and in light of scientific developments, these characteristics turned out to be insufficient to reflect the true state of water quality, as a result of the exploration of physical, chemical, and bacteriological multi-parameters.

The present chapter is dedicated to an in-depth literature review of the main techniques that have been applied to assess water quality using large data sets.

II.1. Different methods of water quality assessment

As with all aspects of the water resources sector, the water quality field has experienced various studies related to the development of efficient techniques of water quality assessment. Traditionally, water quality was assessed by measuring the concentration of parameters that make up a water sample through laboratory analysis and comparing them with their recommended guidelines or standards. Indeed, this procedure may be effective in identifying the factors that may be responsible for water pollution. But it is often very expensive, laborious, and time-consuming, especially with numerous parameters are measured.

In the wake of the latter weakness, the use of advanced mathematical models and approaches has become necessary, particularly for large generated datasets. According to the literature, there are many techniques adopted to assess water quality. In this chapter, we will mention the most commonly used methods and classify them into essential groups as depicted in Figure II.1.

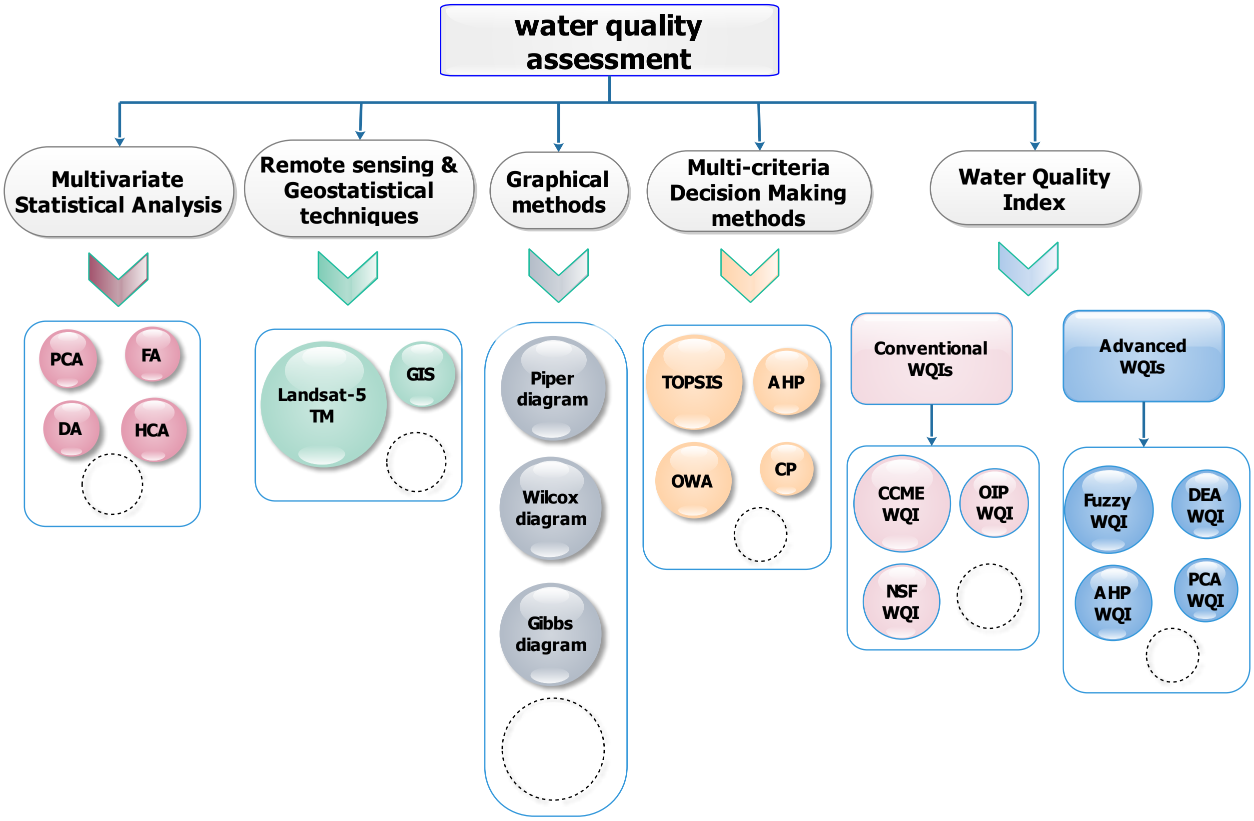

Figure II.1. : Water quality assessment methodologies

II.1.1. Multivariate statistical techniques

They are collections of methods and procedures that analyze, interpret, display, and make decisions based on multivariate data. The foundation of multivariate statistical methods was gradually developed, starting from the beginning of the twentieth century (Yang and Trewn, 2004).

First, we talk about the two popular methods i.e., Principal Component Analysis (PCA) and Factor Analysis (FA). These methods can be used for data reduction, which means that they are very useful for extracting a few hidden factors from a massive amount of multivariate data, and these factors explain most of the variation in the data. The structures of hidden factors can be very useful in finding the fundamental reasons for the variation.

Second, Discriminant Analysis (DA) is a powerful multivariate statistical method for classifying objects or individual units into uniquely defined groups (Shrestha and Kazama, 2007).

Third, Cluster Analysis (CA) is a technique that assembles large objects based on the characteristics they possess. Where the objects that have very similar characteristics are grouped into one cluster and objects with dissimilar features are found in different clusters. Given the large number of studies that have been conducted in the literature using the aforementioned techniques, we just point out a few.

Varol *et al.,* (2012) have investigated the spatiotemporal variations of water quality in the three dam reservoirs of Kralkızı, Dicle, and Batman in the Tigris River basin. They have applied CA, PCA/FA and DA on the data set of 18 physicochemical parameters collected from 10 sampling stations during one year (February 2008 to January 2009).

At the national level, several studies of groundwater quality assessment have proven the potential of multivariate statistical techniques in giving promising results and extracting significant information from big data matrices, such as (Belkhiri et al., 2011; Belkhiri et al., 2010a; Belkhiri et al., 2010b; Belkhiri and Narany, 2015; Bencer et al., 2016; Bouderbala et al., 2016; Ghodbane et al., 2016; Houria et al., 2020; Khelif and Boudoukha, 2018; Semar et al., 2013; Ziani et al., 2016). It is noteworthy that our research scope was mainly devoted to evaluating surface water quality (Dams), in this section, we are going to talk about some Algerian contributions that handled studies related to assessing dams' water quality.

Bouguerne *et al.,* (2017) employed PCA/FA, CA, and DA to assess the temporal variations of water quality at Ain Zada dam (northeast Algeria) through interpreting a dataset of 16 hydrochemical parameters observed during 10 years (2003-2012). As such, PCA and FA methods revealed that the parameters responsible for water quality variations were mainly related to salinization factor and organic pollution. The CA technique in R-mode grouped the 16 variables into 4 clusters of similar water quality characteristics, and in Q-mode 160 samples are grouped into 4 statistical groups where Total Dissolved Solids (TDS) and Volume seem to be major distinguishing factors between variables and years. DA method indicated that only 11 parameters are truly responsible for large variations in water quality, enabling the reduction in the number of sampling variables.

Hamil *et al.,* (2018) have applied a series of multivariate statistical techniques, including PCA/FA, CA, and multiple regression analysis (MRA) On 19 physicochemical parameters dataset over 5 years and from 6 different sites located in and around the lake of Ghrib dam. PCA/FA identifies five dominant factors responsible for the variations in water compounds' concentration. These factors are mainly related to multiple anthropogenic activities, as well as natural processes. Results of MRA clearly showed that runoff raises the concentration of most of the inorganic and organic parameters. CA has given two kinds of clustering results by space and season. The maximum similarity has been shown between the summers and autumn periods and between winters and spring periods. The sampling stations were divided into two distinct groups, the first cluster represented only station (S1) which received pollution from non-point sources from agricultural activities, whereas, the grouping of the other stations in another cluster proves their similarity and confirms the spatial homogeneity of the surface waters in the Ghrib dam.

II.1.2. Remote sensing and geostatistical techniques

In the last few decades, remote sensing and geostatistical techniques have been successfully used in surface water quality monitoring studies. To a better understanding of the concept of these techniques, each one has been described separately.

II.1.2.1 Remote sensing

The principle of this technique is based on the measurement of radiation amount at various wavelengths emitted or reflected from the water's body constituents (Bhattacharya et al., 2018). Different sensors mounted on satellites and aerial vehicles, such as airplanes, can record the reflected/emitted energy, and these reflections, can be used directly to detect different water quality parameters like turbidity, salinity, total phosphorus (TP), Secchi disk depth (SD), temperature, pH, dissolved organic carbon (DOC), etc. or indirectly to process images that provide valuable information on the extent of contamination of water bodies and concentration of contaminants (Haji Gholizadeh et al., 2016).

Remote sensing techniques have been extensively used to evaluate surface water pollution, for instance, Wang and Ma (2001) have used Landsat Thematic Mapper (TM) data and limited sampling data in water quality prediction and assessment in Taihu Lake, which is located in the southern part of Yangtze River Delta, China. Besides, He *et* *al.,* (2008) found a statistically significant correlation among eight measured water quality variables including algae content, turbidity, and concentrations of COD, Total Nitrogen, NH_3–N, NO_3 2–N, Total Phosphorus, and Dissolved Phosphorus and remote sensing data (Landsat-5 TM) in a slightly-polluted inland water body in the Guanting Reservoir.

II.1.2.2 Geostatistical methods

Geostatistical techniques are a powerful tool for studies related to natural resources. As an example, Geographic Information System (GIS) is considered the most widely used technique in the literature because it encompasses the use of computer hardware, software, and geographic data, according to (ESRI, 1990). This integration of topographic features with physical parameters has enabled decision-making and has been commonly utilized to track changes in land use-land cover, changes in population density, housing, and mapping of flooded areas.

GIS database works with different maps or thematic layers that contain different types of information such as elevation, soil type, land use, and population density (Bhattacharya et al., 2018). To name a few contributions, Karakuş (2019) employed the Kriging method which is a regression-based optimum interpolation technique to evaluate the water quality of the Kızılırmak River within the provincial boundaries of Sivas in Turkey. Similarly, Venkatramanan *et al.,* (2016) found that the effect of residual saline water, irrigation, livestock wastes, and municipal sewage was the main contamination source of groundwater quality in Miryang City, Korea.

II.1.3. Multicriteria Decision Making Methods (MCDM)

MCDM, commonly called multi-criteria decision analysis (MCDA), is a tool developed in the field of decision theory to address operational research problems with a limited number of decision options that decision-makers (DMs) must evaluate and rank according to the weights of a fixed set of evaluation criteria (Lu and Ruan, 2007; Mutikanga et al., 2011).

According to the literature, many researchers have recently solved water resource management and planning problems through the application of various MCDA techniques. The most frequently applied methods in water quality surveys are the Order of Preference by Similarity Order of the Ideal Solution (TOPSIS) technique, compromise programming (CP), Analytical Hierarchy Process (AHP), Ordered Weighted Average

(OWA), Elimination and Choice Translating Reality (ELECT), and Preference Ranking and Organizing Method for Enrichment Evaluation (PROMETHEE).

In the last few years, MCDM techniques, have shown promising results, enabling researchers to obtain meaningful information from complex datasets and develop robust indices (Li et al., 2010). Sutadian *et al.,* (2017) employed AHP to estimate the aggregation weights to use with the water quality parameters toward the computation of the WQI. Yousefi *et al.,* (2018) have used TOPSIS, CP, and OWA methods for mitigating the conflicts of WQI ranking among monitored wells of Karaj plain in Iran. They concluded that it is possible to eliminate contradictions in WQI calculation using such models. Mladenović-Ranisavljević *et al.,* (2018) combined the hybrid approach MCDM-WQI for assessing the water quality of Danube River in Serbia by applying PROMETHEE and Geometrical Analysis for Interactive Assistance (GAIA). Whereas, Bouchard *et al.,* (2010) addressed the problem of selecting a drinking water treatment system in Québec, Canada in the light of considering technical and non-technical dimensions using the ELECTRE II method.

II.1.4. Graphical diagrams

Graphical diagrams are commonly used methods to assess water quality for irrigation purposes particularly, they are also capable of representing the hydrogeochemical facies of different water samples (Ravikumar et al., 2015). The overall hydrochemical components of irrigation water may be explained with the most widely utilized diagrams, including Piper, Durov, Stiff, Wilcox, Schoeller, and Gibbs diagrams (Ewaid, 2018).

In Piper's diagram, the percentage concentrations in milliequivalents of the main anions (Cl^-, SO_4^{2-}, and HCO_3^-) and cations (Ca^{2+}, Na^+ K^+, and Mg^{2+}) can be plotted in two triangular fields, which are then further projected into a central diamond field and the chemical composition of the water is deduced. Regarding the Wilcox diagram, it is produced by plotting the sodium hazard (SAR) and salinity hazard (EC), which divides the waters into categories C1, C2, C3, and C4 based on EC and categories S1, S2, S3, and S4 based on SAR. While Gibbs suggested a simple plot of total dissolved solids (TDS) as a function of Na^+ / (Na^+ & Ca^{2+}) weight ratio, this would provide significant information on the relative importance of three major natural mechanisms controlling surface water chemistry: (1) evaporation, (2) precipitation, and (3) water-rock interaction (Stallard and Edmond, 1983). To name a few.

A large number of publications have been found in the literature that used the above diagrams in the context of surface water and groundwater. More recently, in 2019, (Khedidja and Boudoukha) studied the adequacy of groundwater quality in Tadjenanet-Chelghoum Laid in eastern Algeria for irrigation using the Piper and Wilcox diagrams. Ewaid (2018), assessed the water quality of Al-Gharraf Canal in southern Iraq for irrigation purposes using an integrated framework of six diagrams i.e., Piper, Stiff, Schoeller, Durov, Gibbs, and Wilcox supported by AquaChem and RockWork-hydrochemical software.

II.1.5. Water Quality Indices (WQIs)

WQI is simply a based-mathematical approach that expresses the overall status of a water quality sample by a single explanatory value obtained through the integration of complex data sets of WQ parameters (Khan et al., 2003). The use of a WQI was initially proposed by Horton (1965), since then, various indices have been formulated and developed by many researchers such as the US National Sanitation Foundation's Water Quality Index (NSF-WQI) (Brown et al., 1970), Bhargava WQI method (Bhargava, 1983), Canadian Council of Ministers of the Environment's WQI (CCME WQI), British Columbia WQI (CCME, 2001) and Oregon WQI (Cude, 2001), etc.

These indices can be formulated in two ways: the first involving an increase in index values with the degree of pollution, namely Water Pollution Indices (WPIs), and the other relating a decrease in index values with the degree of pollution, i.e. Water Quality Indices (WQIs). The only difference between these two indices resides in the formula used for estimating pollution and the number of parameters considered (Abbasi and Abbasi, 2012). WPIs have been extensively used in most applications pertaining to surface water systems, including river quality.

II.1.5.1. WQI formulation

The formulation and development of the above indices are based on the following four main steps:

II.1.5.1.1. Parameter selection

As in all phases of WQI formulation, choosing an appropriate number of parameters for building-up an effective index is considered a very difficult decision, although, the more parameters are considered, the more accurate the water assessment is, especially if sampling stations measure a large number of parameters up to a dozen hydrochemical constituents. But, the WQI would become unwieldy if every possible parameter was included in the index (Abbasi and Abbasi, 2012). Furthermore, these parameters could cost government companies and stakeholders a lot of money for laboratory analysis operations such as sampling equipment and chemicals, etc. For this reason, the parameter selection step is quite important.

Based on the literature review, most of the developed WQIs have used a minimum number of parameters in a subjective way. As in the case of Horton's index who has selected the 10 most commonly measured water quality parameters. On the other hand, some researchers have attempted to formulate their indices with a minor degree of subjectivity in the parameter selection procedure by using advanced statistical analysis methods. For instance, Tripathi and Singal (2019) have applied PCA to reduce the number of the original data set. As a result, the total number of parameters decreased from 28 to 9. This has been done to make the process more feasible and economic as this would drastically reduce the time, effort, and cost required to monitor samples for a large number of parameters.

II.1.5.1.2. Developing sub-indices

In this step, the different units of water quality parameters should be transformed into a common scale via mathematical functions. Because without such transformation, variables that have unlike metrics may not be incorporated in the final index (e.g., pH and TDS). According to Abbasi and Abbasi (2012), subindices can be classified as one of four general types:

II.1.5.1.2.1. Subindices based on linear functions

The procedure for making up the subindex's value in this type is obviously dependent on the linear equation as following:

$$I = \alpha \times x + \beta \qquad \text{(II.1)}$$

where I is the subindex, x the hydrochemical variable, and a, b the constants. Indeed, linear indices are simple to calculate and easy to understand but have some limitations.

II.1.5.1.2.2. Subindices based on segmented linear functions

This type of subindices is considered as a linear sub-index segmented in different parts, where each part represents a straight-line joined at breakpoints. It is interesting to note that the current sub-index paradigm is clearly consistent with the water quality standards of national and international agencies. For example, WHO guidelines for BOD parameter are classified into four classes, namely [0-5], [5-10], [10-15], and [> 15], which means that the BOD sub-index is segmented into four parts. The segmented linear function can be presented by the following overall equation :

$$I = \frac{b_{i+1} - b_i}{a_{i+1} - a_i}\left(x - a_i\right) + b_i,\ a_i \le x \le a_{i+1} \qquad \text{(II.2)}$$

where x and I coordinates of the breakpoints are represented by (a_1, b_1), ..., (a_j, b_j), with i segments ($i = 1, 2, 3, ..., m.$).

II.1.5.1.2.3. Subindices based on nonlinear functions

Since the relationship between the dependent variable (subindex) and independent variable (parameter) does not vary linearly, it leads clearly to a curvative graph when plotted on a sheet. These non-linear functions are of two main categories:

- Implicit function, which can be plotted on a graph but which does not include an equation.
- Explicit function, which gives a mathematical equation (e.g., exponential function).

II.1.5.1.2.4. Subindices based on segmented nonlinear functions

The segmented nonlinear function is composed of line segments similar to the segmented linear function; however, at least one segment is nonlinear.

II.1.5.1.3. Assignment of weights

Allocating weights to the parameters according to their relative importance is one of the most important steps of WQI development. Typically, weighing techniques have been classified into two broad categories: subjective and objective methods. The objective approach assigns weights to parameters using statistical techniques and natural language reasoning, while subjective methods assign weights to parameters based on the judgment of experts in the field, policymakers, and various stakeholders.

Subjective techniques such as Delphi method (Brown et al., 1970; Smith, 1990), Analytical Hierarchy Process (AHP) (Saaty, 1988; Sutadian et al., 2017) have been characterized by a common disadvantage which is ambiguity in identifying the importance of parameters. Judgment in the case of subjective methods varies according to the opinions, knowledge, and experience of the stakeholder, researcher, or expert, which means WQIs' results are not necessarily unique for the same sample of water sources.

II.1.5.1.4. Calculating the final index

In this step, all the performed subindices will be aggregated to produce the final index. According to (Abbasi and Abbasi, 2012) there are several techniques of subindices aggregation, however, the three most basic ones are:

i. **Additive aggregation:** the subindices, in this case, were combined by a summation operation. This method has been the most widely used by many researchers, e.g. Horton (1965), Brown *et al.* (1970), Prati *et al.* (1971), Dinius (1972), Otto (1978), etc.

ii. **Multiplicative aggregation:** In the same way, this type of aggregation is carried out by combining subindices through product operation such as the indices of Landwehr *et al.*, (1974), Walski and Parker (1974), Bhargava (1983), Dinius (1987).

iii. **Logical aggregation:** For this type of aggregation, the subindices are integrated by a logical operation (e.g., minimum/maximum). As an example, consider Smith's index (1990).

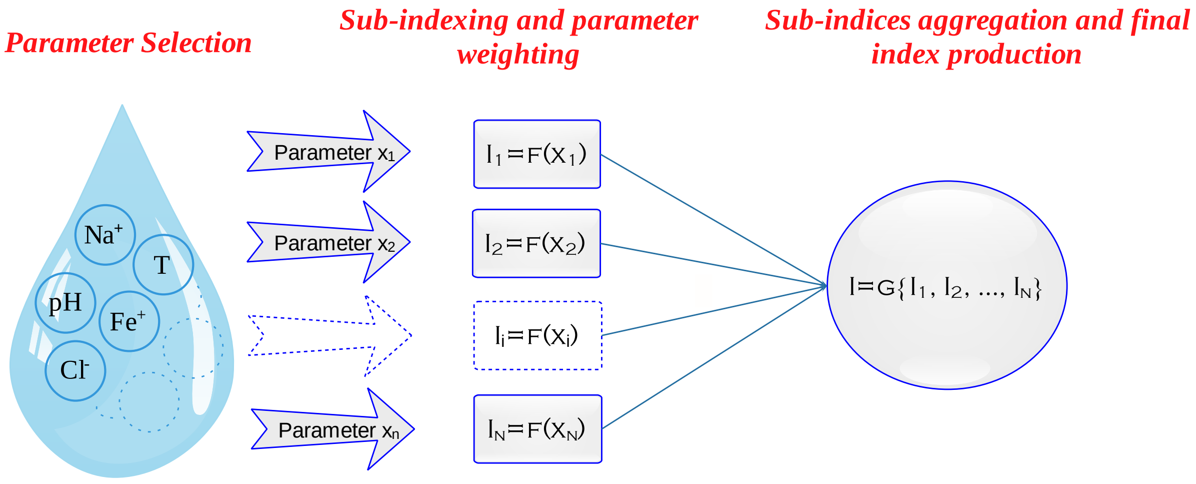

Figure II.1. : flowchart of WQI evolution

II.1.5.2. Conventional WQIs

As mentioned above in Section II.1.5.1., the methodology of WQI development has been subjected to literary criticism either for failing to consider sufficient numbers of selection parameters or for choosing an arbitrary number of variables based on experts' opinions. Besides, assigning weights subjectively to parameters from the judgment of subject specialists and policy-makers using rating curves, and deterministic equations. Given the large number of conventional indices reported in the literature, Table II.1. has been prepared to summarize the most used ones.

Table II.1. Formulation of some conventional WQIs widely used in the literature

Authors	Region	Selected parameters	Weightage procedure	Aggregation function
NSF-WQI (Brown et al., 1970)	USA	(09) parameters, including {DO, Fecal Coliforms, pH, BOD_5, NO_3, Total Phosphates, Temperature, Turbidity, TS}	Derived from the ranking of parameters according to their importance, through the opinion of 142 experts.	Weighted sum index
Prati's WQI (Prati et al., 1971)	Italy	(13) parameters: {DO, pH, BOD_5, COD, Permanganate, SS, NH_3, NO_3, Cl, Fe, Mn, Alkyl Benzene Sulphonates, Carbon Chloroform Extract}	Equal weights to all parameters ($W_i = 1$)	Arithmetic average
Oregon WQI (Cude, 2001)	USA	(08) parameters: {T, DO, BOD, pH, $NH_3 + N\text{-}NO_3$, Total Phosphorus, Total Solids, Faecal Coliform}	Equal weights to all parameters ($W_i = 1$)	Unweighted harmonic square mean

OIP WQI (Sargaonkar and Deshpande, 2003)	India	(13) parameters: {Turbidity, pH, Colour, DO, BOD_5, TDS, Hardness, Cl, NO_3, SO_4, Total Coliform, As, F}	Equal weights to all parameters ($W_i = 1$)	Arithmetic average
CCME WQI (CCME, 2001)	Canada	Non-limited parameters (depending on available data and their standards)	All parameters have the same degree of importance.	Implicit function $I = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732} \right)$

II.1.5.3. Advanced WQIs

In the last decades, several researchers have used advanced statistical methods and artificial intelligence to overcome the aforementioned drawbacks and develop robust indices, relying mainly on natural language reasoning and objective bias in information processing. Indeed, these approaches have yielded promising results, as with those who have employed information entropy (Amiri et al., 2014; Li et al., 2010; Ukah et al., 2020), fuzzy logic (Icaga, 2007; Lermontov et al., 2009; Ocampo-Duque et al., 2006), genetic algorithm (Peng, 2004), stochastic (Beamonte et al., 2005), and self-organizing map (SOM) (Lu and Lo, 2002) methods, etc.

MCDM techniques have also played a key role in enhancing the performance of WQI by achieving a noticeable improvement in the computation process of the weights (Li et al., 2010). Examples of MCDM techniques applied for the computation of WQIs include AHP (e.g., Kavurmaci (2016) and Sutadian *et al.* (2017)), OWA, and TOPSIS (e.g., Zahedi *et al.* (2017)). No matters their contribution to bettering WQIs, it is undeniable that these approaches' outcomes are still reliant on experts' judgment, which underpins the subjective feature of the assessment process (Oukil and Govindaluri, 2020). Some of the indices reported in this section have been described in detail in Table II.2.

Table II.2. Summary of some sophisticated WQIs based on advanced approaches and AI.

Authors	Region	Number of parameters	Applied method	Period study
Li *et al.*, (2010)	China	(26) hydrochemical variables	They used information entropy to improve the procedure for assigning	One month (August 2007)

Amiri *et al.*, (2014)	Iran	(10) parameters namely, Ca^{2+}, Na^{+}, K^{+}, Mg^{2+}, HCO^{3-}, SO_4^{2-}, F^{-}, Cl^{-}, NO3- and EC	weights to each parameter.	One year (2009-2010)
Icaga, (2007)	Turkey	(11) physical and inorganic chemical parameters: T, pH, DO, Cl, SO_4, NH_3, NO_2, NO_3, TDS, Colour and Na	The fuzzy logic approach has been applied to establish the membership functions of each parameter (Fuzzification) and calculate the final index from the result membership functions (Defuzzification)	1991-2005
Ocampo-Duque *et al.*, (2006)	Spain	Five groups of 27 hydrochemical parameters	They employed the Fuzzy Inference System (FIS) to develop the FWQI by using the hybrid Fuzzification-Defuzzification process and AHP to generate relative weights for each parameter	2002-2004
Peng, (2004)	China	(30) water quality parameters	He has implemented the approach of Genetic Algorithm and Compromise Active Function to optimize (a and b) parameters in the formula of WQI and allocate weights to each water parameter respectively.	Five years (1991-1995)

Beamonte *et al.*, (2005)	Spain	(21) physicochemical variables	The authors proposed a stochastic quality index that takes into account the uncertainty surrounding the quality classification, It is constructed with the probability classification vector of each parameter which is obtained by a mixed-lognormal model	Not available
Lu and Lo, (2002)	Taiwan	They selected Total Phosphorous (TP), Chlorophyll α (chl α), and Secchi disk depth (SD) for their research	Lu and Lo have used the Fuzzy Synthetic Evaluation (FSE) results to train self-organizing maps (SOMs) and obtain deeper insights into the reservoir water-quality data.	Five years (1987-1992)
Kavurmaci and Üstün, (2016)	Turkey	(19) hydrochemical parameters	The authors proposed a hybrid approach involving AHP to obtain the weights assigned to each criterion via experts' judgments and DEA to determine the WQI.	May 2012
Zahedi *et al.*, (2017)	Iran	(13) Physicochemical parameters	They implemented TOPSIS and CP techniques to explore and rectify the probable errors of WQI tool in the classification of water quality classes.	2002-2014

Conclusion

Because of population growth, land use, and agricultural and industrial practices, water quality is threatened by severe pollution. For this reason, several monitoring systems have been set up to collect data that can provide important information on sources of pollution. Furthermore, such a large number of observational parameters can be formulated using sophisticated tools to express overall water quality in numerical, symbolic, and colorful results.

Based on the latter perspective, we conducted a review of methods commonly used in the literature to assess water quality, such as Multivariate Statistical methods, Remote Sensing and Geostatistical techniques, Multi-criteria Decision-Making methods, Graphical techniques, and Water Quality Indices. Due to the promising results of the application of WQI in previous studies, the WQI has been comprehensively presented.

Part II

Materials and Methods

Chapter III:
Description of the study area

Introduction

The section of study area description is considered indispensable because it enables researchers and readership to recognize the main environmental characteristics prevailing in the region while providing a global overview and relevant information on the geographical, topographical, and climatic aspects that have an impact in somehow on the phenomenon of water quality deterioration.

The present thesis is devoted to studying the whole of northern Algeria with a vast area of about 225,105 Km^2, which represents the essential part of the country in terms of the number of inhabitants and mega infrastructures as dams' projects.

In addition to the presentation of the different environmental aspects of this study area, two further important issues were discussed. The first one shows the different methodologies followed by ANRH to assess water quality in Algerian dams. The second axis highlights the data obtained and a thorough description of the Spatio-temporal variation of sampling sites.

III.1. Location of the study area

The studied area is located in the northern part of Algeria, which is characterized by a significant number of constructed dams and reservoirs compared to the southern side due to the noticeable difference in rainfall level. It comprises the four hydrographic basins in the Tellian region i.e., Oranie-Chott-Chergui (OCC), Cheliff-Zahrez (CZ), Algerois-Hodna-Sommam (AHS), and Constantinois-Seybousse-Mellegue (CSM) with a global area of 225 105 Km^2, extending between longitudes 2°13'48 ''W and 8°40'12 ''E and latitudes 37°7'12 ''N and 32°44'24 ''N as shown in Figure. III.1.

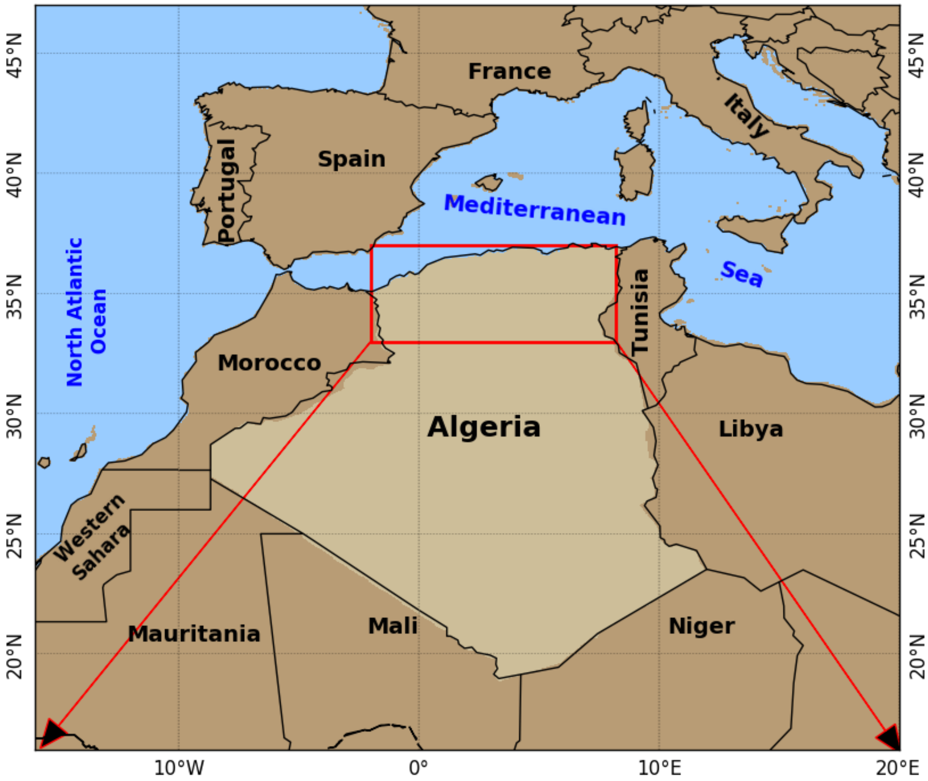

Figure III.1. : Geographical location of the study area

The study area is bordered by the Mediterranean Sea to the north, Tunisian borders to the east, Sahara hydrographic basin to the south, and Moroccan borders to the west.

III.2. Topographic overview

The relief of this area is enjoyed by a non-uniform structure and heterogeneous topography, with three distinct areas (see, Figure III.2). Tellian Atlas in the North and Saharian Atlas in the South have formed in parallel two large massifs, approaching each other towards the East and between which are inserted vast plains and Highlands.

Highlands compartment offers a landscape of steppes, with an altitude varying between 600 and 1000 m in the west and between 800 and 1000 m in the east, they stretch for about 200 km to 500 km from east to west respectively over a width of 100 to 200 km (Rezak et al., 2012).

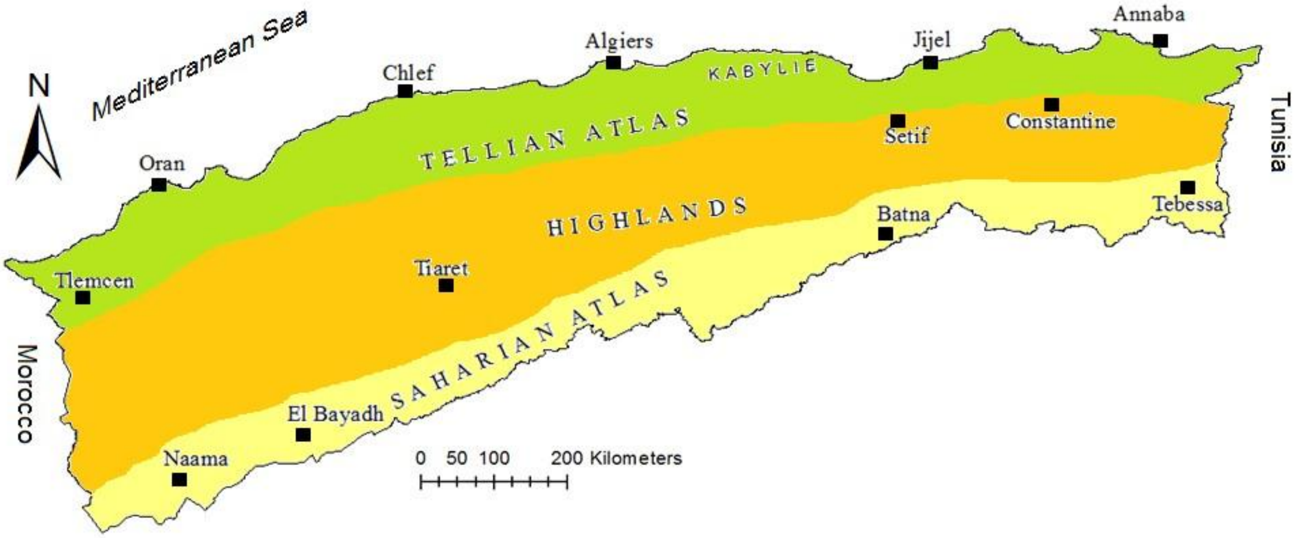

Figure III.2. : Topography of the study area (Source: Taïbi, 2016)

In the Tellian Atlas part, we find the famous mountain range of Oursenis, Dahra, and Trara to the west. In the North, we also find the massif of Djurdjura which culminates at the peak of Lala Khadîdja (2308 m), and the crystal massif of Edough in the East. In the South, the Titteri Mountains rise, followed by the Guergour massif and the Ferdjioua Mountains. These latter are extended by the mountains of Constantine and Medjerda (Taïbi, 2016).

Along the Tellian Atlas coastline, there are fertile coastal plains and valleys such as the plains of Cheliff and Sidi Bel Abbes in the West, Mitidja in the Center, and Seybousse in the East.

The Saharian Atlas is considered as a natural boundary between the North and South over a distance of about 700 km. It consists of a discontinuous series of mountains. In the west, we have the mountains of Ksour (1980 m), Amour (1683 m), and Ouled Nail (1500 m) and in the east, we have Mount Aurès (2328 m) (Meddi and Toumi, 2014).

III.3. Climate and Rainfall

The study area has a very varied climate. the mild Mediterranean climate of the northern coast, with a wet winter and hot summer. the semi-arid climate of the highlands and mountains, 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 (Soltani et al., 2021).

The Saharian Atlas is characterized by a very hot and dry climate in summer, soft in winter with less rainfall compared to the North because of its distance from the sea. The average annual rainfall varies from one region to another, particularly between the north and the highlands and between the east and west of the study area (Meddi and Toumi, 2014).

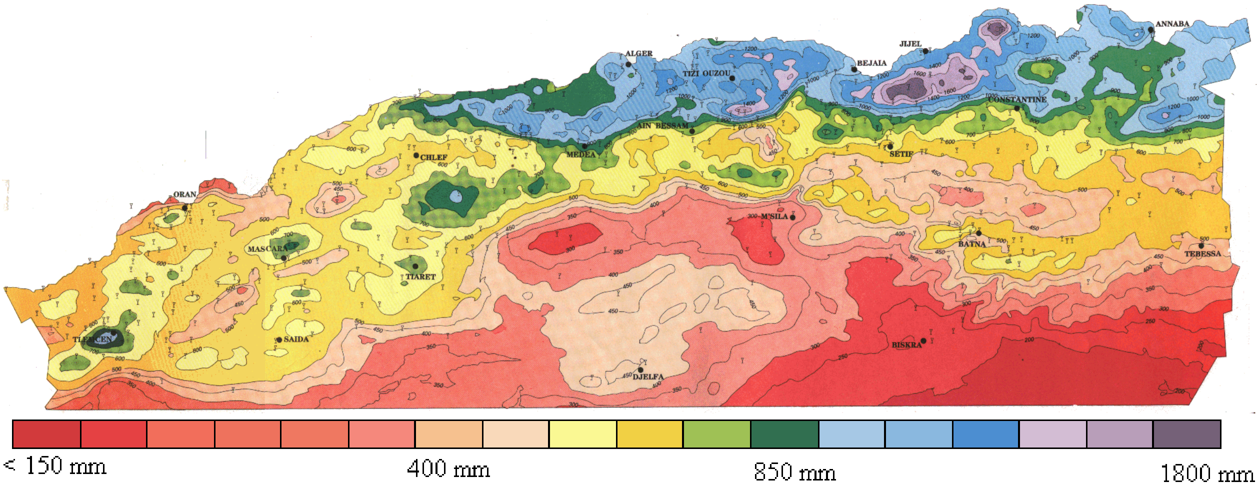

Figure III.3. : Rainfall map of Northern Algeria (Source: ANRH, 1993)

Rainfall in Algeria increases from west to East and decreases from north to south, where rainfall generally reaches the threshold of 400 mm in the west, 700 mm in the center, and 1000 mm in the east (Figure III.3). While the rainfall rate varies between 600 and 1000 mm in the coastal part, between 400 and 600 mm in the highlands, and is < 100 mm in the Sahara (ANRH, 2016).

III.4. Data collection

The implementation of an effective monitoring system is considered a crucial source of data acquisition of hydrochemical parameters measurement because without such a step water quality assessment can not be done. In Algeria, the National Agency of Water Resources (*Agence Nationale Des Ressources Hydraulique, ANRH*) has the primary responsibility for doing this task.

ANRH is a public institution with administrative, scientific, and technical vocation, which manages multi-monitoring networks of surface and groundwater quality across the national territory in order to:

- Preserving the national water resources from potential factors of pollution by implementing the developed tools of laboratory analysis and in-depth interpretation.
- Providing a better understanding of raised issues in each watershed.
- Designing appropriate models for evolutionary management of the resource, both qualitative and quantitative.

Furthermore, ANRH operates 07 national laboratories located in the provinces of Algiers, Constantine, Oran, Blida, Ouargla, Adrar, and Djelfa, with which to meet the several demands in terms of chemical, bacteriological and hydrobiological analyses at a sampling capacity of 4 0,000 samples per year.

Due to various activities that ANRH carries out, in this thesis, we try to summarize only their main missions of surface water quality monitoring.

III.4.1. Monitoring of quality parameters

Since 1984, ANRH has established a monitoring network covering all the dams intended for drinking water supply as well as the main rivers of the country (Figure III.4). This network is composed of 124 stations geographically attached to the three regional branches (Central, East, and West) :

- 40 stations in the central regional branch.
- 45 stations in the western regional branch.
- 39 stations in the eastern regional branch.

The frequency of sampling at one site varies from one sample per month to one sample per week during the summer. The present network supplies database on the different measured and observed hydrochemical parameters. Where the maximum number of monitored parameters reaches 26 variables.

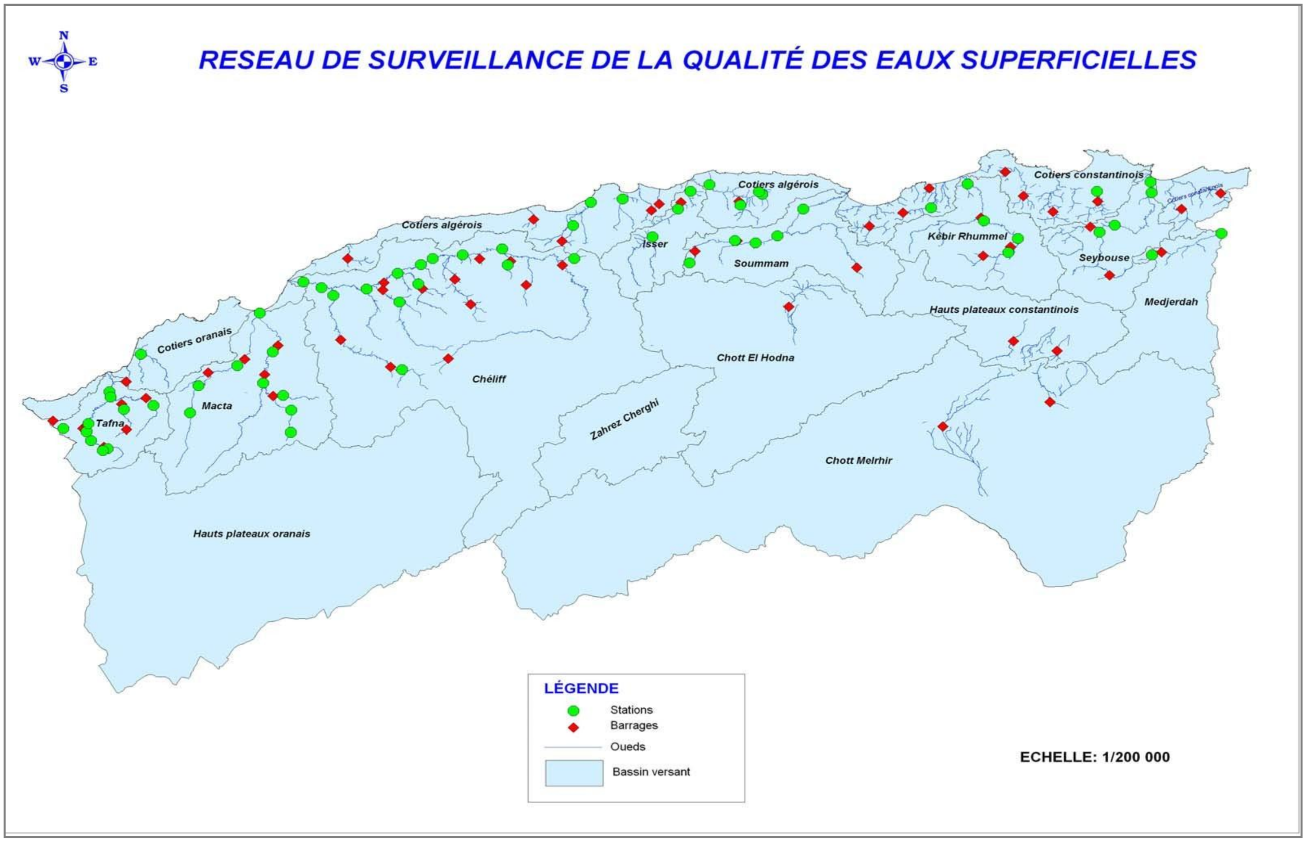

Figure III.4. : Surface water quality monitoring network (Source: ANRH, 2009)

III.4.2. Water quality mapping methodology

ANRH defines water quality according to four quality classes including :

- Class I: Good water quality, used without special requirements; it is represented graphically by the color *Blue*.
- Class II: Medium water quality, used after simple treatment. It is represented in *Green*.
- Class III: Poor water quality, can only be used after very extensive treatment. It is represented in *Yellow*.
- Class IV: Unsuitable water quality (excessive pollution), can only be used after specific and very expensive treatments. It is shown in *Red*.

The assessment of quality is determined from a double-entry grid (quality class / measured parameters), by evaluating each hydro-chemical parameter with respect to its standard (see Tables III.1, 2, 3, and 4). This evaluation includes only a few parameters, which are certainly important, but which do not cover all forms of pollution. From a practical viewpoint, it can be seen that this process is very effective in identifying the variables that contribute to the degradation of water quality. for example, the hyper concentration of both grids (nitrogen and phosphorus) are likely to reveal the eutrophication risk of dam reservoirs, which leads subsequently to blooms of algae during the summer period. However, it reflects only a minor view of the general state of the water.

Table III.1. Ranges of water quality standards of the basic parameters

Parameter	Class I	Class II	Class III	Class IV
Classification of Mineral Quality				
TS (mg.L^{-1})	300 - 1000	1000 - 1200	1200 - 1600	> 1600
Ca^{2+} (mg.L^{-1})	40 - 100	100 - 200	200 – 300	> 300
Mg^{2+} (mg.L^{-1})	< 30	30 - 100	100 – 150	> 150
Na^{+} (mg.L^{-1})	10 - 100	100 - 200	200 - 500	> 500
Cl^{-} (mg.L^{-1})	10 - 150	150 - 300	300 - 500	> 500
SO_4^{2-} (mg.L^{-1})	50 - 200	200 - 300	300 - 400	> 400
Classification of Organic Quality				
DO (%)	90 - 100	50 - 90	30 - 50	< 30
BOD_5 (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

III.4.3. Water quality estimation

The overall quality of water samples is estimated by comparing the results of analyses with the different quality standards (grids) based on the 90% principle:

- ✓ for less than 10 measurements, the worst value determines the quality class.
- ✓ for 10 or more measurements, we eliminate 10% of the values judged as exceptional, and the worst of the remaining values determines the rank.

Table III.2. Grid of different phosphorus concentrations

Phosphate	P1	P2	P3	P4
PO_4^{3-} (mg.L^{-1})	≤ 0.01	0.01 – 0.1	0.1 - 3	> 3

Pi: level of phosphorus pollution

III.4.4. Determining a quality class to a stream

The quality assigned to a certain stream is estimated at specific points which are then generalized to sections of the stream following the direction of water flow.

Table III.3. Concentration grid of Nitrogenous compounds

Parameter	N1	N2	N3	N3
NH_4^+ (mg.L^{-1})	≤ 0.01	0.01 – 0.1	0.1 – 3	> 3
NO_2^- (mg.L^{-1})	≤ 0.01	0.01 – 0.1	0.1 – 3	> 3
NO_3^- (mg.L^{-1})	≤ 10	10 - 20	20 - 40	> 40
NTK (mg.L^{-1})	≤ 2	2 - 3	3 - 10	> 10

Ni: level of nitrogen pollution

III.4.5. Estimation of quality in the lack of measurements

The quality of certain rivers and streams is sometimes estimated without being measured, it can then be estimated in two ways:

- They report the quality of the old map
- They estimate the quality based on the knowledge of the discharges and their evolution and taking into account the developments carried out such as the realization of WWTP,... etc.

The quality of these rivers is represented in dotted lines on the map.

Table III.4. Grid used to report problems with toxic and undesirable elements

Toxic elements	M1	M2	M3	M4
Fe (mg.L^{-1})	0 – 0.5	0.5 – 1	1 – 2	> 2
Mn (mg.L^{-1})	0 – 0.1	0.1 – 0.3	0.3 – 1	> 1
Cr (mg.L^{-1})	0	0 – 0.05	0.05 – 0.5	> 0.5
Cu (mg.L^{-1})	0 – 0.02	0.02 – 0.05	0.05 – 1	> 1
Zn (mg.L^{-1})	0	0 – 0.5	0.5 – 1	> 1
Cd (mg.L^{-1})	0	0	0 – 0.01	> 0.01
Pb (mg.L^{-1})	0	0	0 – 0.05	> 0.05
F^- (mg.L^{-1})	0	0 – 0.8	0.8 – 1.5	> 1.5
Cn^- (mg.L^{-1})	0	0	0 – 0.02	> 0.02
Phenols (mg.L^{-1})	0 – 0.002	0.002 – 0.02	0.02 – 1	> 1
Det (mg.L^{-1})	0 – 0.3	0.3 – 0.5	0.5 – 3	> 3

Mi: level of toxic and undesirable elements pollution

III.4.6. Sampling sites

According to the National Agency of Dams and Transfers (*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 47 large dams and reservoirs with a disparity in the number of measured parameters and their monitoring period. These dams are located in the major northern watersheds, i.e. OCC, CZ, AHS, and CSM (Figure III.1), where the characteristics of each watershed have been summarized in Table III.5.

Table III.5. The capacity of studied dams in the 04 regional hydrographic basins

Hydrographic Basin	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

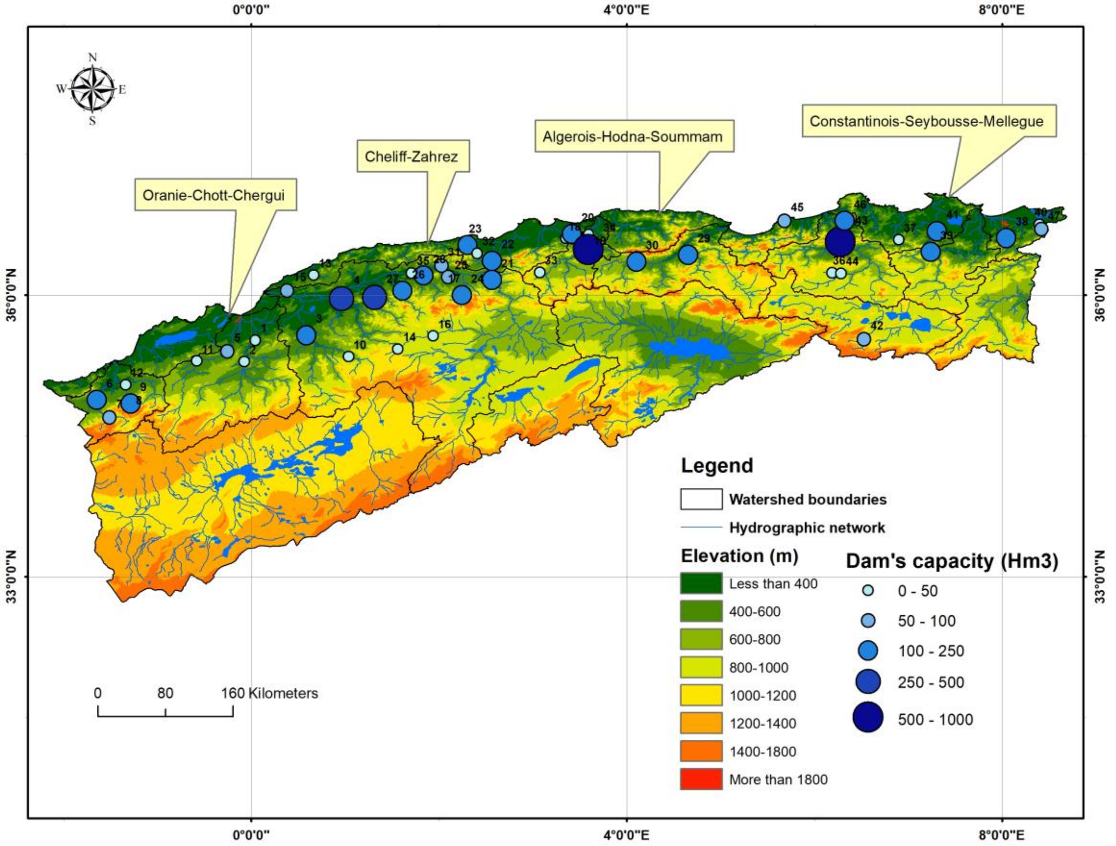

Figure 4.5. : Sampling sites of water quality parameters

As mentioned above, due to the lack of consistency in the database of selected dams, our contribution related to the assessment of Algerian dams' water quality was divided into two case studies. The first case contains 47 dams defined with 10 hydrochemical parameters over 11 months (January to November). The second study is devoted to shedding light on the most important dam among those stated before, given its largest intake capacity and strategic location, namely Beni Haroun dam. The water quality of this infrastructure is studied in parallel with its upstream by using 22 parameters observed over a long period of 11 years (2000 to 2010). The name, operating year, capacity, and other characteristics of each dam are described in Chapter I, Table 2.

Conclusion

The study area involves the North Algerian part with a total area of about 225,105 Km^2 covering the four major watersheds of the country including OCC, CZ, AHS, and CSM. Since this area is characterized by a vast surface, relief, climate, and precipitation diversify from one region to another. For instance, the average rainfall varies according to the East-West and North-South trends as it increases from west to east and decreases from north to south.

In this thesis, we are studying the water quality of forty-seven (47) dams whose datasets have been collected from ANRH with remarkable variation in the number of parameters and sampling time. There are two scenarios of the study area: The first one includes 47 dams defined with 10 hydrochemical parameters over 11 months (2019). While the second study is represented by the Beni Haroun dam with 22 parameters observed over a long period of 11 years (2000 to 2010).

Chapter IV:

Overview of the used approaches

Introduction

As water quality degradation has become a serious issue in the field of water resources management, the implementation of an effective monitoring system is necessary to track potential pollution indicators as well as spatial and temporal variations in water quality parameters. Typically, the assessment of water quality in any water body is done only by conventional laboratory analysis and then by comparing each parameter against its standard.

In fact, this process is often very laborious and time-consuming, especially with multi measured parameters. Moreover, extracting meaningful information from the resulting dataset and exploring latent relationships among the analyzed variables is considered a major challenge for water decision-makers. Therefore, the use of sophisticated tools and modern techniques is considered a very useful way to solve the above-mentioned difficulty and ensure relevant analysis.

This chapter focuses on the presentation of techniques and the definition of approaches used for a better understanding of their conceptual framework in terms of multivariate statistical analysis including Principal Component and Factor Analysis (PCA/FA), Water Quality Index (i.e., CCME WQI), Trend Analysis viz. Man-Kendall test, clustering methods as K-means algorithm and Data Envelopment Analysis (DEA).

IV.1. Definitions

IV.1.1. K-means clustering

The *"Clustering"* terminology refers to a very broad set of techniques for finding sub-groups, or clustering groups. Among them, we have employed the K-means clustering because it is a simple and elegant partitioning method, developed by (MacQueen 1967), widely used in many scientific fields due to its concise algorithm and efficient application. K-means clustering aims basically to split a data set of n independent observations, each defined by p measured parameters into K distinct clusters. If x_{ij} denotes the value of parameter j as taken by observation i $(i = 1,2,..., n;\ j = 1,2,..., p)$, each observation is assigned to a particular cluster k (Weatherill and Burton 2009).

K-means algorithm deploys over the following steps:

a) Specify the number of clusters K.

b) Select randomly K grid cells from the data set as the initial cluster centers i.e., centroids $c_k\ (k = 1,..., K)$.

c) Calculate the distances from each grid cell to the K centroids, and assign the grid cells to the closest centroid c_k.

d) Calculate the mean of the grid cells in each cluster, and transfer the K centroids to the mean of their cluster.

e) Reassign the grid cells that are the closest to the new centroid c_k to cluster k.

Repeat Steps (a) to (e) until the objective function converges to a minimum (Shi and Zeng 2014).

The objective function is expressed as $$J = \sum_{k=1}^{K} \sum_{g \in k} \left| x_g^{(k)} - c_k \right|^2 \qquad \textbf{(IV.1)}$$

where $x_g^{(k)}$ denotes the g^{th} grid cell that belongs to k^{th} cluster and c_k is the average of n_k grid cells belonging to k^{th} cluster, which is calculated as follows: $$c_k = 1/n_k \sum_{g=1}^{n_k} x_g \qquad \textbf{(IV.2)}$$

As an example below, **Figure IV.1.** shows the sequence of the k-means algorithm, from the initial phase of choosing the number of clusters, which here is K=3, to the final result of the clustering, through numerous calculation steps and iterations.

As shown in **Figure IV.1.** the top left plot i.e., (a): represents the n observations of a data set. (b): each observation is randomly assigned to a cluster. (c): the cluster centroids are computed and are shown as large colored circles. The centroids are mostly overlapped because the first cluster assignments were chosen at random. (d): each observation is assigned to the nearest centroid. (e): once again, the cluster centroids are calculated, leading to new ones. (f): the results obtained after ten iterations.

In most K-means clustering applications, the preferred metric is the Euclidean squared distance (Hartigan and Wong 1979). However, determining the optimal number of clusters K remains the main drawback (Ay and Kisi 2014). Many approaches have been suggested to address this vexing problem such as Dunn's index (1974), Davies-Bouldin's index (1979), Kaufman's index (1990), and the *"Gap statistic"* function of Tibshirani *et al.* (2001) to mention just a few.

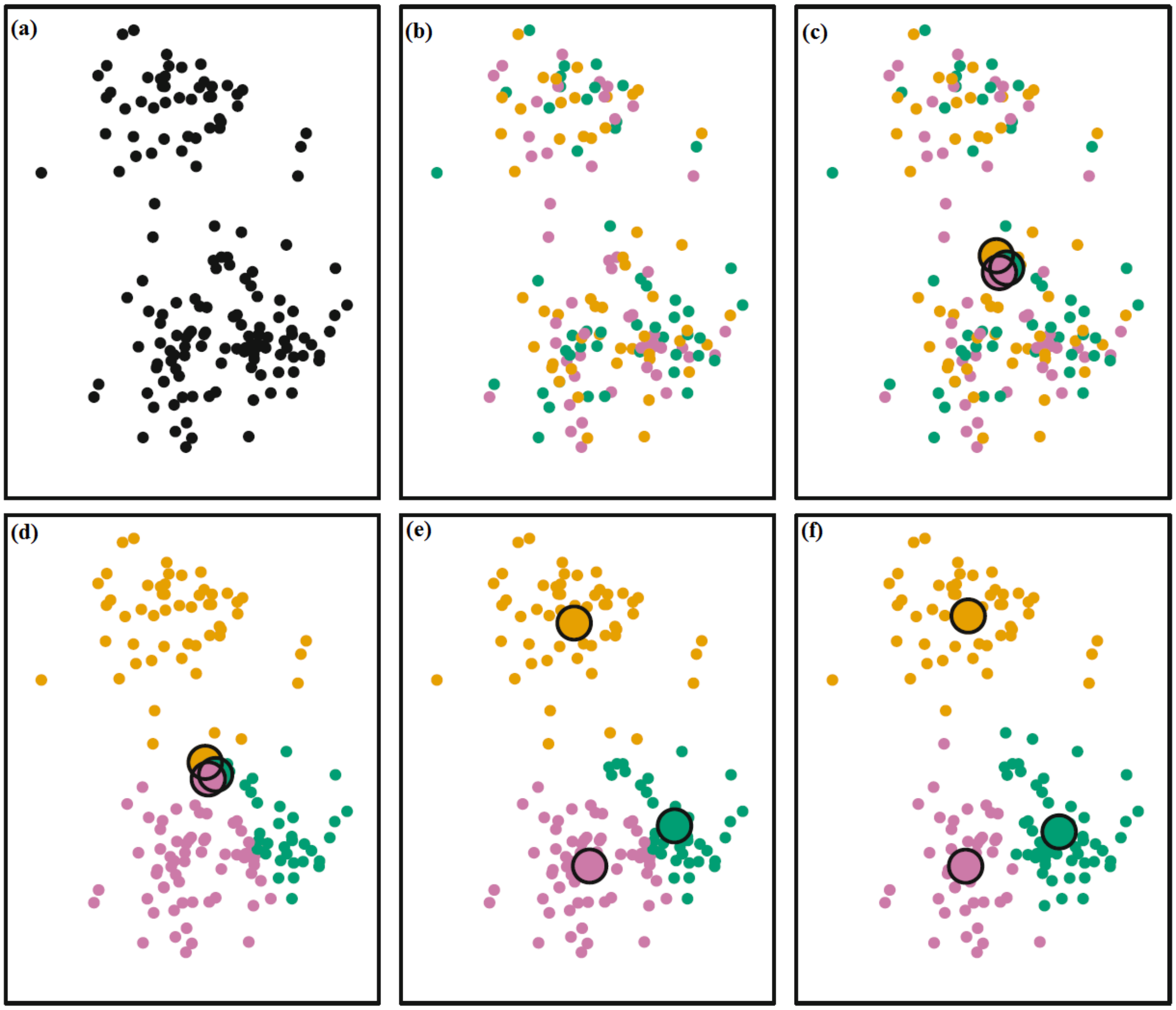

Figure IV.1. : Plot of the K-means algorithm sequence

IV.1.2. Principal Component Analysis and Factor Analysis

Principal components analysis (PCA) and Factor Analysis (FA) are probably the two popular approaches for deriving a low-dimensional set of features from a large set of variables (James *et al.* 2013). PCA is designed to transform the original variables into new uncorrelated axes, i.e., Principal Components (PCs), arranged in decreasing order of importance. These PCs are obtained by multiplying the original correlated variables with the "eigenvectors" that have been extracted from the correlation and covariance matrix (Varol *et al.* 2012). PC can be expressed as follows:

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + \ldots + a_{im}x_{mj} \qquad \textbf{(IV.3)}$$

where z is the component score, a is the component loading, x is the measured value of variable, i is the component number, j is the sample number and m is the total number of variables.

PC provides information on the most meaningful variables that describe the whole data set through data reduction with a minimum loss of original information (Singh *et al.* 2004). Though PCA and FA techniques are strongly related, they are not identical (Zarei and Pourreza Bilondi 2013).

FA reduces the contribution of less significant variables in order to further simplify the data structure coming from PCA, and the new group of variables, known as varifactors (VFs), is extracted by rotating the axis defined by PCA (Shrestha *et al.* 2008). PC is a linear combination of observable water quality variables, whereas VF can include unobservable, hypothetical, and latent variables (Helena *et al.* 2000).

Accordingly, a small number of factors will generally represent about the same amount of information as the much larger set of original observations and FA can be expressed as:

$$z_{mn} = b_{f1}f_{1n} + b_{f2}f_{2n} + b_{f3}f_{3n} + \ldots + b_{fk}f_{kn} + e_{fn} \qquad \textbf{(IV.4)}$$

where z is the measured variable, b is the factor loading, f is the factor score, e is the residual term accounting for errors or other sources of variation, m is the factor number, n is the sample number and k is the total number of factors.

IV.1.3. Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI)

The computation of the CCME-WQI, originally known as the Canadian Water Quality Index (CWQI) (Lumb *et al.* 2006), is based on three factors: Scope (F1), Frequency (F2), and Amplitude (F3).

F1 is the proportion of parameters that do not meet their guidelines, known as "failed variables", computed as

$$F1 = \left(\frac{\text{Number of failed variables}}{\text{Total number of variables}} \right) \times 100 \qquad \textbf{(IV.5)}$$

F2 is the percentage of individual tests that do not meet the objectives i.e., "*failed tests*" relative to the total observed parameters. F2 is calculated as follows:

$$F2 = \left(\frac{\text{Number of failed tests}}{\text{Total number of tests}} \right) \times 100 \qquad \textbf{(IV.6)}$$

F3 is a function of individual "excursions" and normalized sum of excursions "*nse*", where an excursion is the number of times an individual concentration is greater than the upper limit of the given threshold (or less than the lower limit).

If the failed test value violates the upper limit,

$$excursions_i = \left(\frac{\text{Failed test value}_\text{i}}{\text{Threshold}_\text{j}} \right) - 1 \qquad \textbf{(IV.7)}$$

If the failed test value violates the lower limit

$$excursions_i = \left(\frac{\text{Threshold}_\text{j}}{\text{Failed test value}_\text{i}} \right) - 1 \qquad \textbf{(IV.8)}$$

Hence, $$nse = \frac{\sum_{\text{i}=1}^{\text{n}} \text{excursion}_\text{i}}{\text{Number of tests}} \qquad \textbf{(IV.9)}$$

and F3 is an asymptotic function that scales *nse* to a value between 0 and 100.

$$F3 = \left(\frac{\text{nse}}{0.01\,\text{nse} + 0.01} \right) \qquad \textbf{(IV.10)}$$

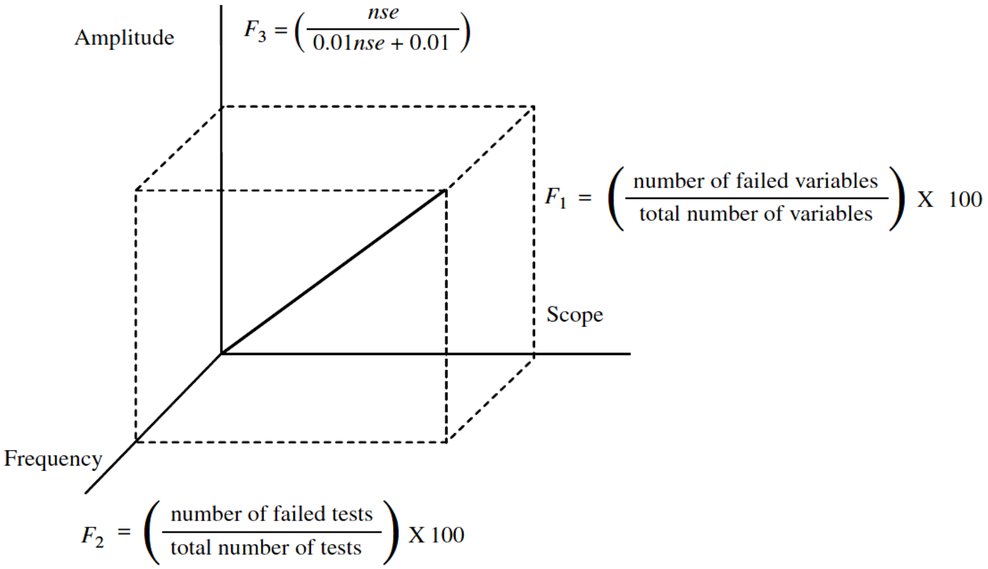

Figure IV.2. : 3D graphical representation of the three factors of CCME-WQI

Finally,

$$\text{CCME WQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right) \quad \textbf{(IV.11)}$$

The factor of 1.732 arises because each of the three individual index factors can range as high as 100. This means that the vector length can reach $\sqrt{100^2 + 100^2 + 100^2} = \sqrt{30,000} = 173.2$ as a maximum. Division by 1.732 brings the vector length down to 100 as a maximum (Abbasi and Abbasi 2012).

CCME-WQI produces a number between 0 (worst water quality) and 100 (best water quality), divided into five categories that can be assigned to the water body as shown in **Table IV.1.**

Table IV.1. CCME WQI categorization schema; CCME (2001)

WQI range	Category Rank	Description
95-100	Excellent	Water quality is protected with a virtual absence of threat or impairment; conditions very close to natural or pristine levels; these index values can only be obtained if all measurements are within objectives virtually all of the time.

80-94	Good	Water quality is protected with only a minor degree of threat or impairment; conditions rarely depart from natural or desirable levels.
65-79	Fair	Water quality is usually protected but occasionally threatened or impaired; conditions sometimes depart from natural or desirable levels.
45-64	Marginal	Water quality is frequently threatened or impaired; conditions often depart from natural or desirable levels.
0-44	Poor	Water quality is almost always threatened or impaired; conditions usually depart from natural or desirable levels.

IV.1.4. Trend Analysis (Mann-Kendall test)

Unlike conventional parametric tests, which must satisfy the assumptions of normality, linearity, independence, seasonality, and missing values to detect statistically significant trends in natural and artificial time series, the non-parametric Mann Kendall (MK) test depends on the difference in sign between all combinations of previous and subsequent data measures.

MK test verifies the null hypothesis (H_0) that a given time series does not exhibit a monotonous trend (increasing or decreasing) (Şen 2017). MK test statistic S is calculated using the given equation:

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\operatorname{sgn}(x_j-x_i) \qquad \textbf{(IV.12)}$$

Where n is the number of data points. x_j and x_i are the the successive measurements of data in time series *i* and *j*, where *j* >*i*, respectively and $\operatorname{sgn}(x_j-x_i)$ is the sgn function as:

$$\operatorname{sgn}(x_j-x_i)=\left\{\begin{matrix} +1 & \text{if} & (x_j-x_i)>0 \\ 0 & \text{if} & (x_j-x_i)=0 \\ -1 & \text{if} & (x_j-x_i)<0 \end{matrix}\right\} \qquad \textbf{(IV.13)}$$

For $n \geq 10$ the variance $V(S)$ is given as:

$$v(s) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i - 1)(2t_i + 5)}{18} \qquad \textbf{(IV.14)}$$

Where *n* represents the total number of data points in the time series dataset. *m* is the number of tied groups. A tied group is a set of sample data having the same value. t_i refer to the number of observations in the i*th* group.

When the total sample size is more than 10, the following equation is used to compute Zs value:

$$Z_S = \begin{cases} \frac{s-1}{\sqrt{v(s)}} & \text{if} \quad S > 0 \\ 0 & \text{if} \quad S = 0 \\ \frac{s+1}{\sqrt{v(s)}} & \text{if} \quad S < 0 \end{cases} \qquad \textbf{(IV.15)}$$

A positive value of Zs indicates an upward trend while a negative value of Zs shows a downward trend direction.

The trend is considered insignificant if Z_{MK} is less than the standard normal variate $Z_{\alpha/2}$, at α % significance level. The trend is significant if $Z_{MK} \geq Z_{\alpha/2}$.

IV.1.5. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric approach was first introduced by Charnes, Cooper and Rhodes (CCR) (1978). It is a relatively new "data oriented" approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs), which convert multiple inputs into multiple outputs.

Because it requires very few assumptions, DEA has also opened up possibilities for use in cases that have been resistant to other approaches because of the complex nature of the relations between the multiple outputs involved in DMUs.

In the literature, researchers in different fields have quickly recognized that it is an excellent and easily used approach for modeling operational processes for performance evaluations (Cooper *et al.* 2011).

The key principle of conventional DEA models like CCR and Banker, Charnes and Cooper (BCC) (1984) is to consume fewer inputs to produce more outputs while evaluating the performance of a DMU (Cook *et al.* 2014). It projects each DMU onto the production frontier of DEA and compares the degree of deviation of DMU from the DEA frontier to evaluate their relative efficiency (Xiang *et al.* 2016).

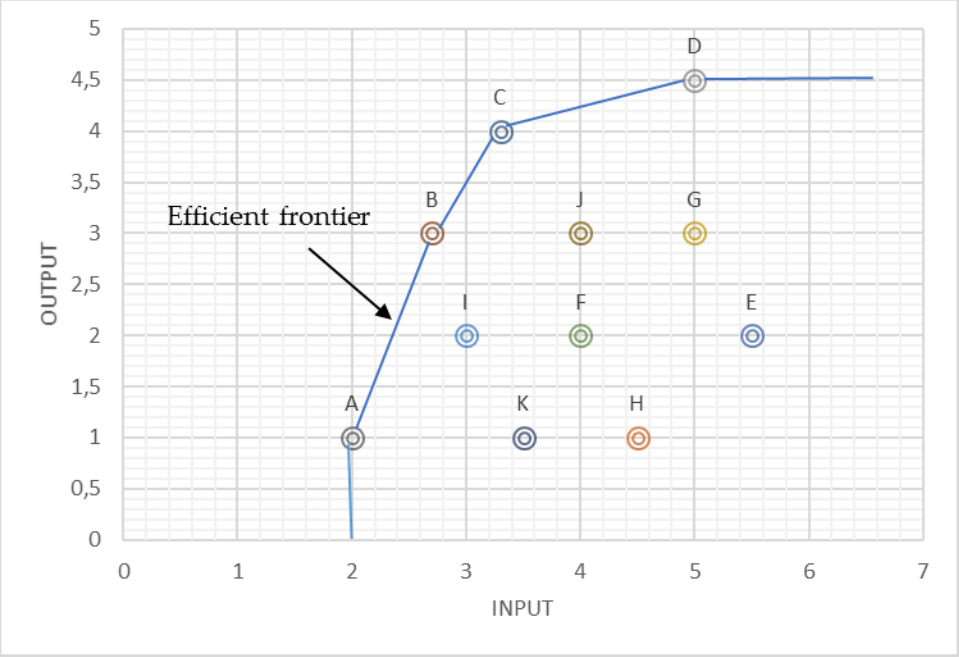

Figure IV.3. : Graphical presentation of production frontiers of (BCC) model

As shown in Figure IV.3. the four DMUs viz. A, B, C and D depict the efficient frontier of the DEA model. The production possibility set is the area consisting of the frontier together with observed or possible activities with an excess of input and/or a shortfall in output compared with the frontiers. All points on the connecting lines A and B, and B and C, and C and D are BCC-efficient DMUs whereas the remaining ones represent inefficient DMUs.

BCC model was used in this thesis to devise a new DEA-WQI for assessing dams' water quality. Accordingly, a dam can be regarded as a DMU that employs, as inputs, the water quality parameters, to produce a single output, which is, here, WQI.

Typically, each input, treated implicitly as a resource of a production process, does necessarily comply with the preference dictum "less is better". In dealing with water quality parameters, the latter dictum does not apply for some of them like Dissolved Oxygen (DO) and pH, etc. Although it accommodates well enough most of the other parameters as NO_3^-, NO_2^-, BOD, and so on. 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 parameter is associated with separate clusters of water quality standards.

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.

To overcome these drawbacks, we have created new input variables called "optimistic closeness values" which are derived on the grounds of the observed values of physicochemical parameters.

IV.1.5.1. Defining new input variables

Assume a set of K dams, each dam d defined with N water quality parameters 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 parameters 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 parameter 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 would support the viewpoint that each parameter 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.

- $A_E = [a_i, +\infty[$ and $x_{id} < a_i \Rightarrow s_{id} = a_i - x_{id} + \varepsilon$ **(IV.16)**
- $A_E = [a_i, b_i]$ and $\begin{cases} x_{id} < a_i \Rightarrow s_{id} = a_i - x_{id} + \varepsilon \\ x_{id} > b_i \Rightarrow s_{id} = x_{id} - b_i + \varepsilon \end{cases}$ **(IV.17)**
- $A_E =]-\infty, b_i]$ and $x_{id} > b_i \Rightarrow s_{id} = x_{id} - b_i + \varepsilon$ **(IV18)**

A 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 $x_{id} \in A_E$.

According to the aforementioned scenarios, it appears that the 1st scenario i.e., equation (16) matches only the parameters that promote the "more is better" dictum as

DO. 2nd scenario (17) depicts the bounded range i.e., pH case, and 3rd scenario applies to all parameters support the "less is better" concept viz. BOD, COD, and PO_4^{3-} etc.

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 parameters i, using observed values x_{id}, for $i = 1,\ldots,N$.

IV.1.5.2. Devising a new DEA-WQI

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 :

$$
\text{(DEA-WQI)}\quad
\begin{aligned}
& E^*_{dd} = \min \theta \\
& \textit{subject to} \\
& \quad \sum_{k=1}^{K} \lambda_{kd} s_{ik} \le \theta s_{id} \qquad i = 1,\ldots,N && \textbf{(IV.19)} \\
& \quad \sum_{k=1}^{K} \lambda_{kd} y_{1k} \ge y_{1d} && \textbf{(IV.20)} \\
& \quad \sum_{k=1}^{K} \lambda_{kd} = 1 && \textbf{(IV.21)} \\
& \qquad \lambda_{kd} \ge 0 \qquad k = 1,\ldots,K
\end{aligned}
$$

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.

Constraints (IV.19) and (IV.20) indicate that reference points for dam *d* are linear combinations of efficient peers. By considering a single constant output, the set of constraints (IV.20) reduces to a single constraint $\sum_{k=1}^{K} \lambda_{kd} \geq 1$. Since the latter includes the convexity constraint (IV.21), 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 $\boldsymbol{\lambda}_d = (\lambda_{1d}\ \lambda_{2d} \ldots \lambda_{Kd})$ provides the weights of the peers in producing the projection of dam *d* on the efficiency frontier. Let $\boldsymbol{\lambda}_d^* = (\lambda_{1d}^*\ \lambda_{2d}^* \ldots \lambda_{Kd}^*)$ 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. 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.

Conclusion

Given a large number of dams to be studied in this contribution, the recourse to advanced approaches and sophisticated statistical techniques is considered as an optimal solution to extract significant information from big data analysis and relationships among the merged complex variables.

The present study was devoted to the examination of the water quality of 47 dams distributed along the northern part of Algeria. This work is divided into two parts. The first part presents a new methodology based on the DEA approach to assess the water quality of 47 dams with a dataset of 10 parameters over 11 months (2019).

The second part is designed to use a group of techniques integrated within the same conceptual framework, namely the PCA/FA, the CCME WQI, the Mann Kendall test, and K-means clustering on a dataset of 22 hydrochemical parameters of Beni Haroun dam and its upstream over 11 years (2000-2010). These two methodological frameworks were briefly illustrated in Chapters V and VI respectively.

Part III

Results and Discussion

Chapter V:

Water quality assessment of 47 Algerian dams using the new based-DEA WQI

Introduction

Water Quality Index (WQI) is one of the most powerful tools for summarizing all hydrochemical variables into a single value. Since Horton (1965) proposed the first modern WQI, many scientists and agencies have attempted to develop robust indices that are suitable and free of criticized drawbacks, including limitations in the number of selected parameters, lack consideration of uncertainties, and subjective and deterministic formulations of the indices in the equation. Most recent research has shown that the application of artificial intelligence and advanced approaches have overcome some of the above-mentioned shortcomings, for instance, Multi-Criteria Decision-Making (MCDM) methods via Analytical Hierarchy Process (AHP) have been used to estimate the weights of all water quality parameters involved in the WQI calculation, as demonstrated in Sutadian *et al.,* (2017) study.

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).

In this chapter, 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 four hydrographic basins of the northern region, Algeria. Accordingly, this work is intended to achieve the following:

i. Produce a new national-based-DEA WQI for stakeholders in the water resources sector to determine the spatial-temporal variations and trends in dams' water quality.

ii. Create nationally an effective water quality benchmarking system by assigning a proper WQI to each dam.

iii. Allocate funds to the water treatment plants in sites and regions that are most affected by polluting resources.

iv. Offers a prioritization procedure for vulnerability assessment of water resources.

V.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 EC, (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 V.1 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.

Table V.1. Drinking WQS of physicochemical parameters

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

V.2 Descriptive analysis of measured parameters

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 dams, distributed over the four hydrographic basins as shown in Figures V.1 and V.2.

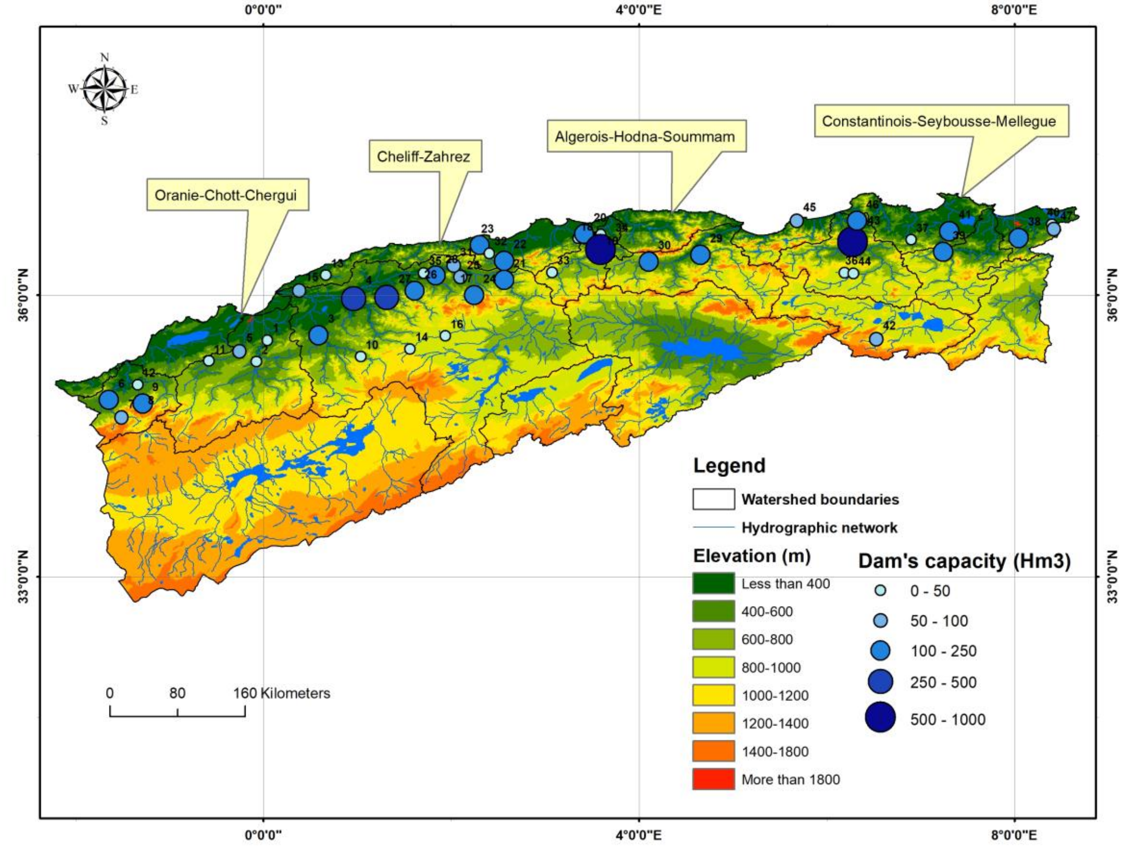

Figure V.1. Sampling sites of water quality parameters

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 V.2 provides the original values of the water quality parameters measured over 11 months.

Table V.2. 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

The observations in Table V.2 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.

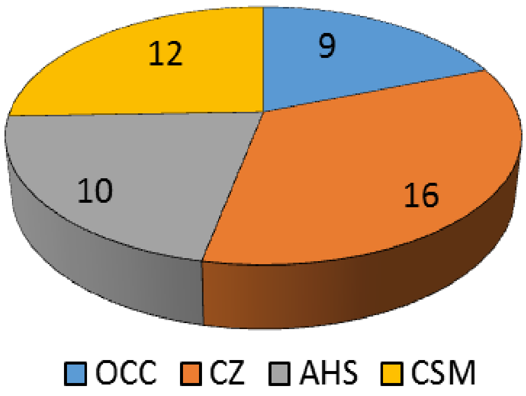

Figure V.2. Frequency of the dams per hydrographic basin

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, we were only able to acquire the available parameters.

V.3 Methodological framework

In order to devise the new WQI, we develop the DEA-based approach depicted in **Figure V.3**

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.

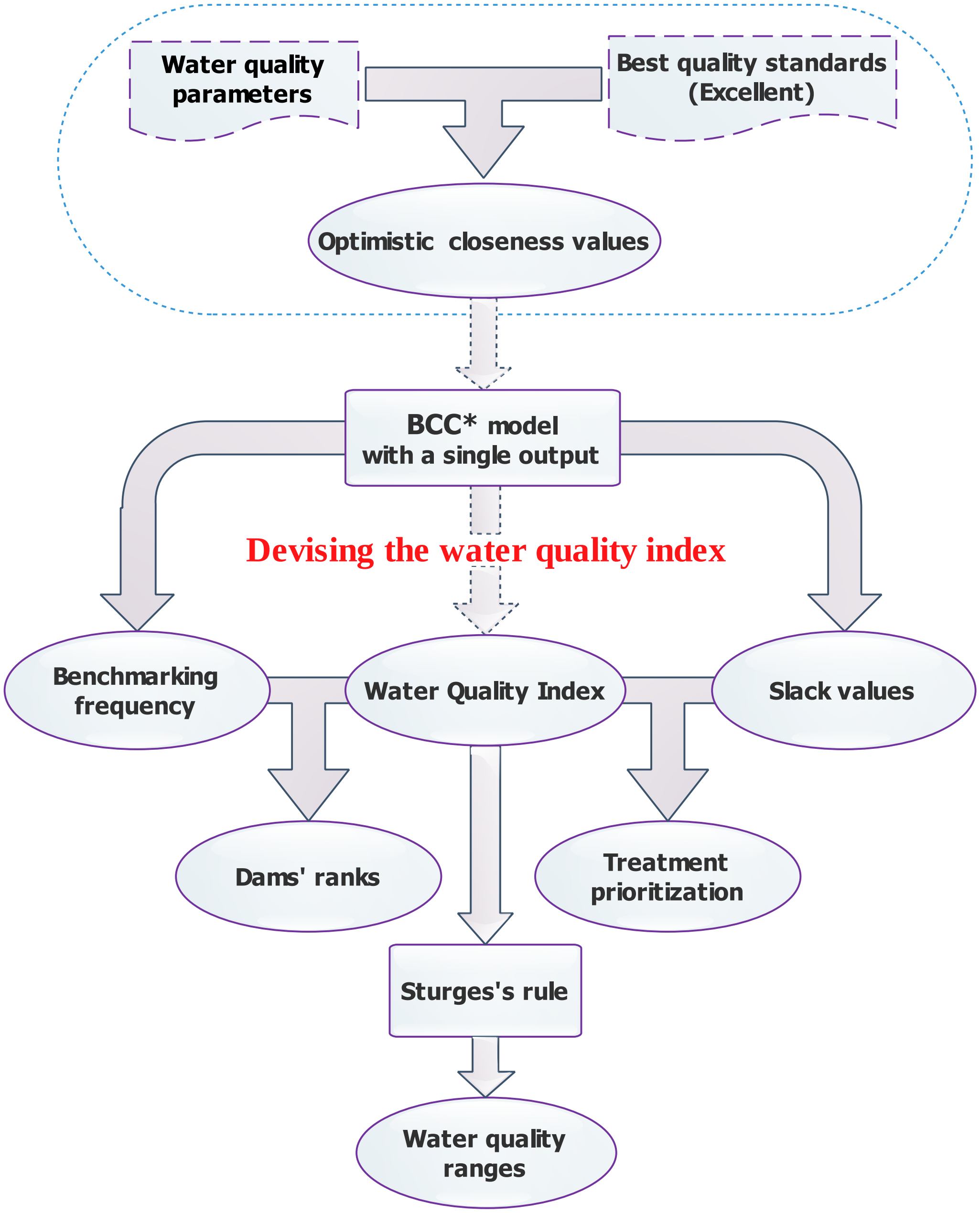

Figure V.3. Conceptual framework of the new WQI generation methodology

V.3.1 Computation of the new input variables

As noted in Section V.2., 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 a 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. $x_{id} = \underset{t=1,\ldots,11}{worst}\left(x_{id}^{t}\right)$, where $worst$ can be max or min, depending on the parameter i.

To better illustrate the meaning of the optimistic closeness value s_{id}, let us consider the parameter 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".

The measured values x_{id} of the water quality parameters and their corresponding optimistic closeness values s_{id} are given in Tables V.2 and V.3 respectively.

Table V.3. 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

D27	0	300	2.80	0	0.673	0.12	0.296	9.0	0	2.0
D28	0	185	5.00	0	0.686	0.19	0.357	7.0	6	2.8
D29	0	0	29.7	0	0.127	0.29	0.143	1.0	6	1.0
D30	0.10	0	34.2	0	0.333	0.35	0.112	6.0	13	5.0
D31	0	0	1.30	0	0.162	0.09	0.296	0	9	0
D32	0	0	21.5	0	0.059	0.22	0.388	3.0	10	1.0
D33	0.20	0	42.8	0	0.813	1.44	0.480	8.0	19	5.5
D34	0	0	28.1	0	0.264	0.19	0.112	1.0	5	7.0
D35	0	0	7.90	0	0.223	0.21	0.786	7.0	13	1.0
D36	0	236	19.02	10	2.111	2.55	1.470	5.0	66	14.4
D37	0	0	5.78	0	0.152	0.36	0.060	0	19	2.4
D38	0	0	9.91	0	0.188	0.15	0.030	0	17	2.0
D39	0	0	0	0	0.210	0.18	0.030	0	24	3.5
D40	0	0	8.62	3	0.087	0.15	0.040	0	15	2.8
D41	0	0	0	0	0.093	0.21	0.380	0	12	3.1
D42	0	0	9.56	0	0.127	0.10	0.030	0	15	2.7
D43	0	0	0.83	0	0.200	0.11	0.050	0	15	3.7
D44	0	0	15.38	0	0.136	0.14	0.020	0	21	3.7
D45	0	0	0	0	0.018	0.02	0.020	0	8	0.6
D46	0.09	0	0.59	0	0.080	0.04	0.040	0	0	0.6
D47	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

It is important to note that the computation of optimistic closeness values s_{id} is context-dependent. The values in Table V.3 are based on drinking WQS and, hence, they are not necessarily the same if the study context is irrigation water performance where different WQS are available (Zahedi, 2017).

V.3.2 Computation of the DEA-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 V.4.

Table V.4. Benchmarking results

Dam	WQI^*_d	Reference set	B_d	Rank
D01	0.2358	D34 (0.212), D45 (0.133), D46 (0.655)	0	41
D02	0.3507	D27 (0.092), D29 (0.361), D34 (0.077), D45 (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

The average WQI is $\overline{WQI} = 66.06$, with a standard deviation $\sigma_{WQI} = 30.53$ revealing a high level of inefficiency among the dams. As bold-highlighted, 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 V.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 V.4 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 IV.1.5.2 in chapter IV, 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 V.4. 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 note that the results provided in Table V.4 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.

V.3.3 Spatial distribution of WQIs

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 Figure V.4.

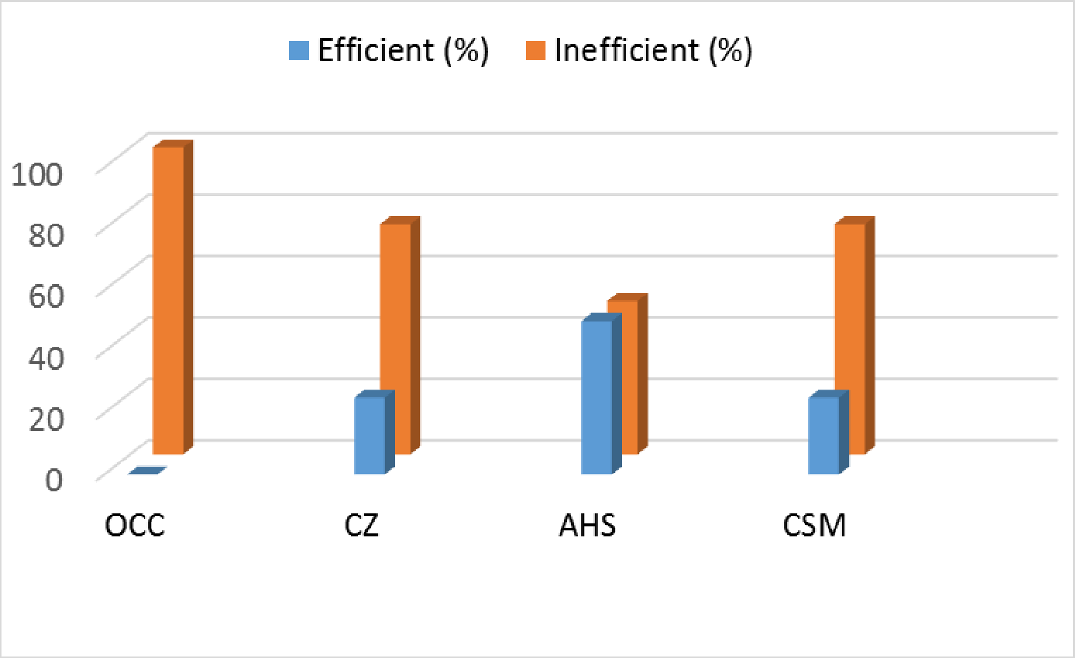

Figure V.4. Efficiency distribution of the dams over the major basins

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 $\overline{WQI}_{CSM} = 64.7$ and $\overline{WQI}_{CZ} = 64.1$. All OCC basin's dams are found inefficient, with $\overline{WQI}_{OCC} = 36$ 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 $\overline{WQI}_{AHS} = 71.8$.

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.

V.3.4 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:

$$I = 1 + 3.322\ \log_{10}(K) \qquad \text{(V.1)}$$

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 $R = \max_{d=1,..,47}(WQI_d) - \min_{d=1,..,47}(WQI_d)$, 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 Figure V.5

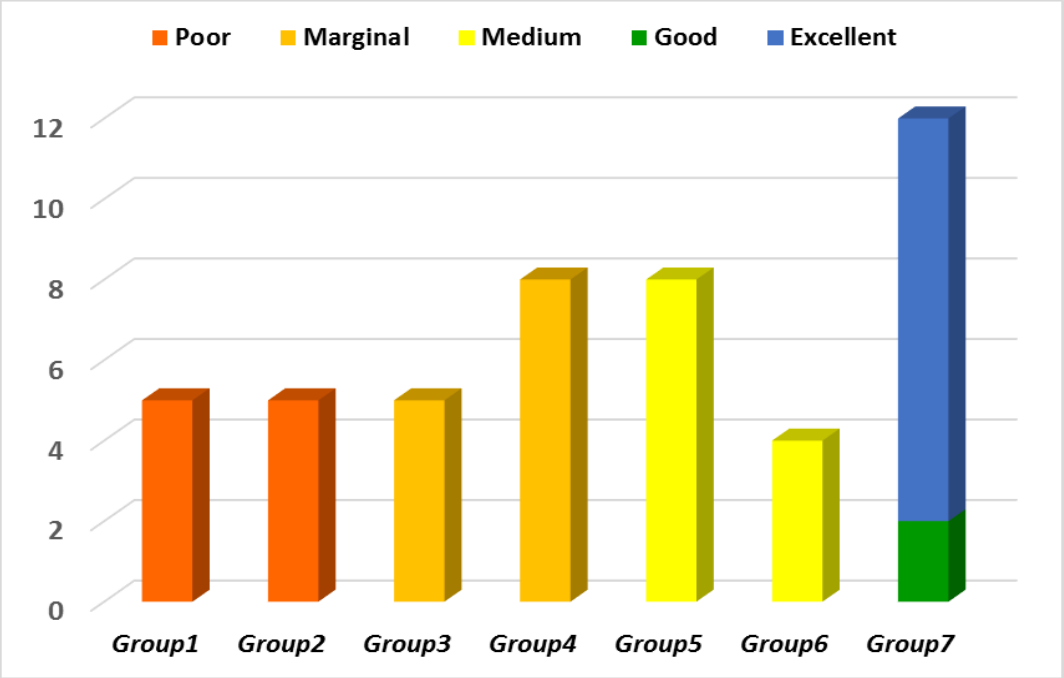

Figure V.5. Frequency distribution and water quality categorization of the dams

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

Table V.5. 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},
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},

33-60	Marginal	D_{30}, D_{02}, D_{03}, D_{37}, D_{08}, D_{21}, D_{24}, D_{47}, D_{25},
0-32	Poor	D_{16}, D_{06}, D_{14}, D_{36}, D_{05}, D_{33}, D_{01}, D_{12}, D_{19},

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

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 Figure V.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.

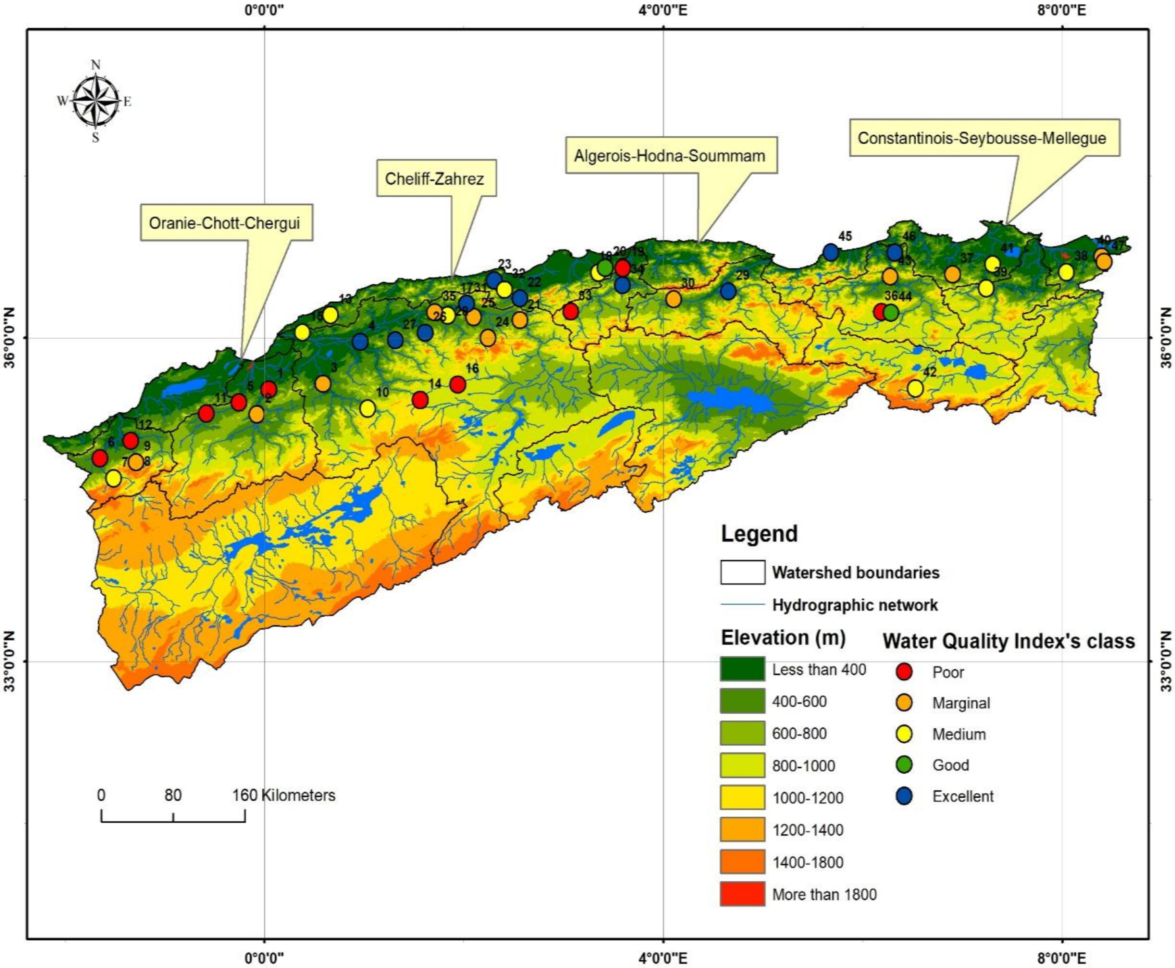

Figure V.6. : Spatial variation of WQIs

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. Nonetheless, man-made practices have also played a key role in the current dire situation. According to Hamlat et al., (2013) 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 (ABHOCC, 2006a).

Meanwhile, the provinces of Mascara, Saïda and Sidi Bel Abbes have a sewage flow of about 126,916 m^3/d (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, Figure V.6 shows that 5 out of 10 excellent water quality dams are found in the AHS basin.

V.4 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 a 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 be 1: Poor, 2: Marginal, 3: Medium, 4: Good, and 5: Excellent. The centroid C_g represents the average WQI of the dams within the class g, as shown in Table V.6.

Table V.6. 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

Furthermore, the box plots 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.

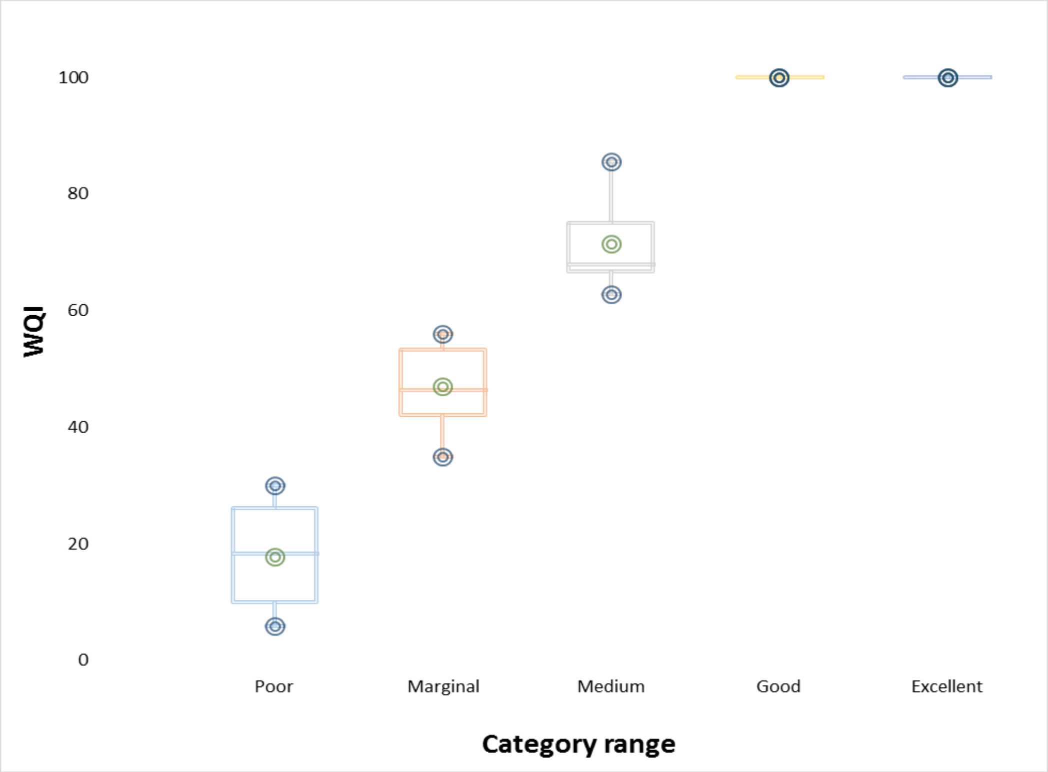

Figure V.7. Box plots of the dams WQI within each category range

V.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 V.7 provide the required reduction associated to each parameter i for each dam d.

Table V.7. Slack values of the hydrochemical parameters

Dam	pH	TS	DO	NO_3^-	NO_2^-	NH_4^+	PO_4^{3-}	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

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 V.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 dam D_{01}, a valid treatment sequence is PO_4^{3-}→ NH_4^+→ NO_2^- → OM→ DO→ 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 develop 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 amount of slack value γ_{id}^* to target for each parameter i, $z_{id} \le \gamma_{id}^*$, $i = 1,...,10$.

V.6 Sensitivity analysis

Risk estimates are input-based, that is, any variation in the water quality parameters can affect not only the dams' 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 developed model was assessed for the worst scenario, adopted as a standard for the whole study (refer to Section V.3.1). 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. Figure V.8 depicts the WQIs obtained under the two scenarios.

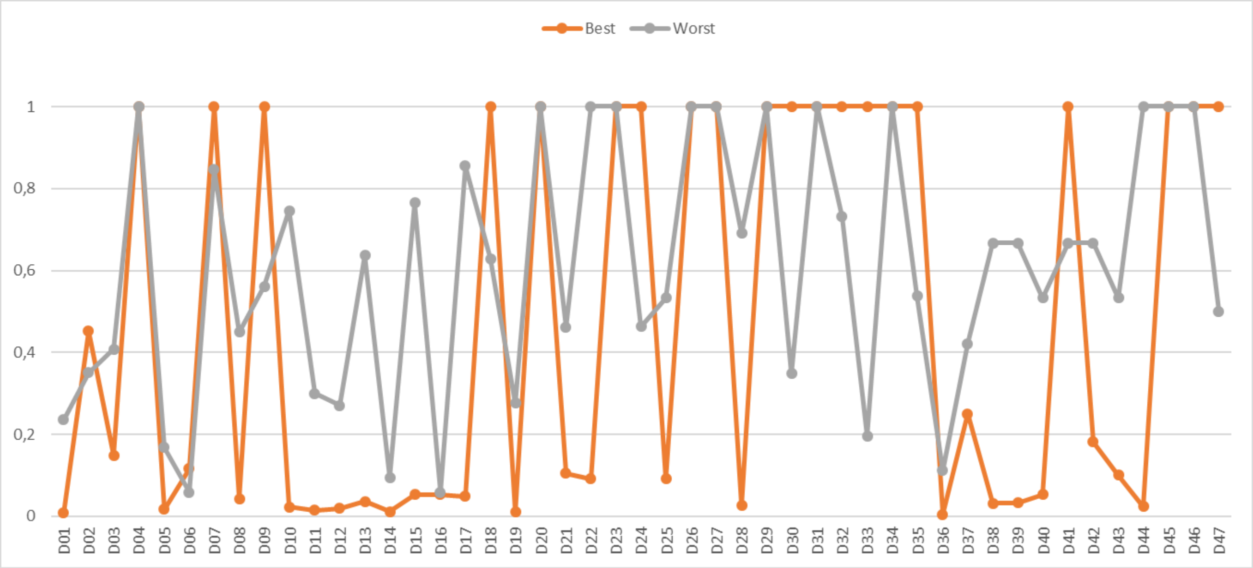

Figure V.8. Variation of WQIs in Best and Worst scenarios

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 more than 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 behavior 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 ranking 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 V.8.

Table V.8. 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

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.

For a closer examination of the WQIs' sensitivity to monthly variations, the dams are ranked within each watershed, and the resulting rank patterns are presented in Figures V.9 to V.12.

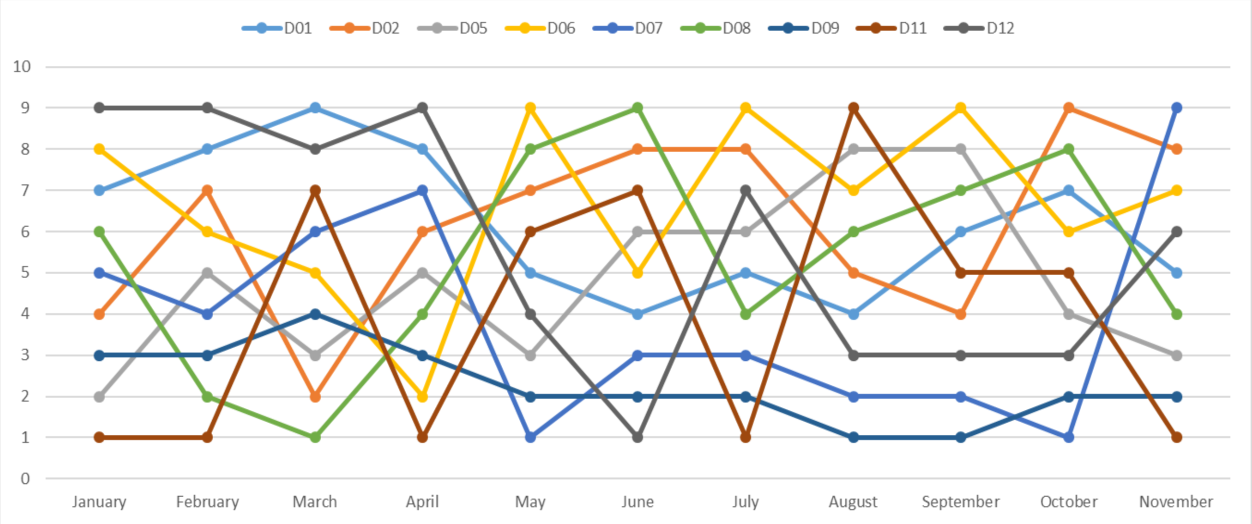

Figure V.9. Monthly ranking of dams within OCC watershed

With only a few exceptions, the dams' rankings within each watershed are fluctuating over the year. However, Figure V.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.

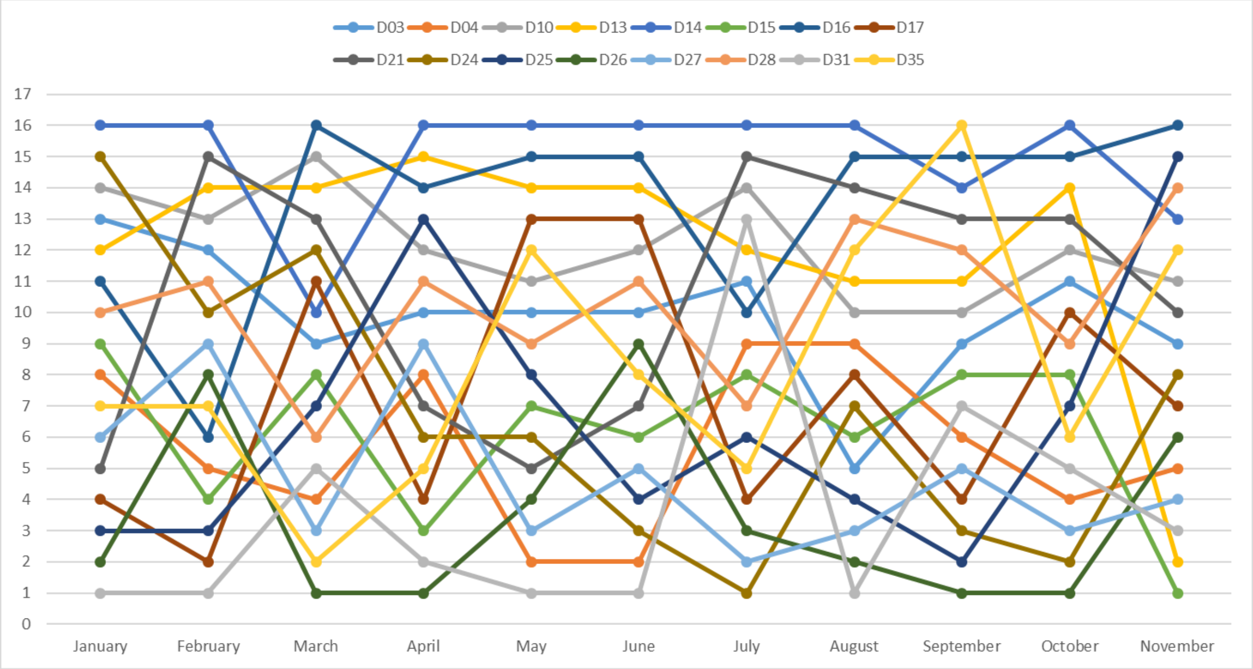

Figure V.10. Monthly ranking of dams within CZ watershed

The situation is not so different in CZ watershed, as shown in Figure V.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}.

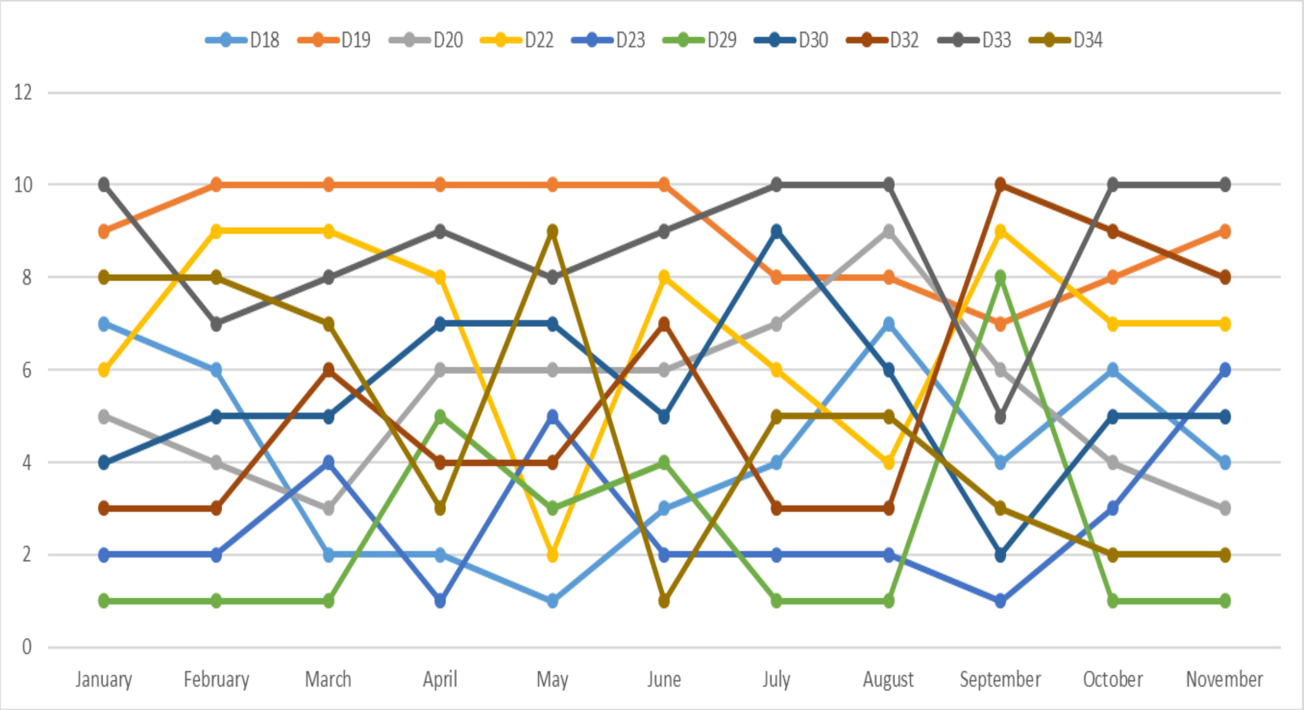

Figure V.11. Monthly ranking of dams within AHS watershed

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

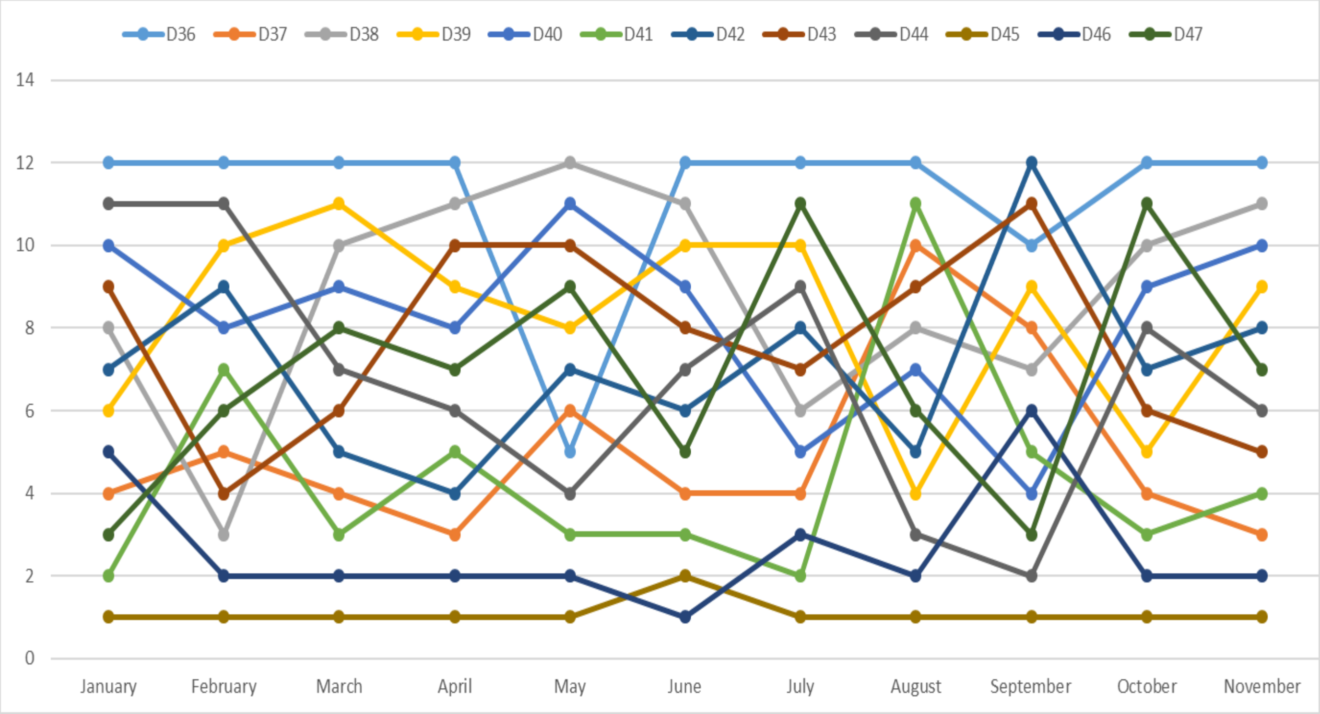

Figure V.12. Monthly ranking of dams within CSM watershed

Figure V.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. The tactical and strategic decisions may however rely on the worst scenario.

Conclusion

In light of the increasing deterioration of water quality in recent years, relying on a robust WQI to assess different water bodies has proven to be an extremely important method, by which can merge all measured variables into a single score. In this chapter, we have proposed a new index based on DEA model to evaluate the WQ of 47 Algerian 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 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 $AHS \succ CSM \succ CZ \succ OCC$ 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.

Chapter VI:
An integrated approach for assessing the water quality of Beni-Haroun dam

Introduction

Due to its strategic location and the abundance of water that often exceeds the nominal capacity, Beni-Haroun (BH) dam plays a key role in an area where it is deemed the core of an interconnected system of five dams, along with the other dam reservoirs *"Boussiaba"*, *"Oued Athmenia"*, *"Koudiat M'douar"*, and *"Ourkis"*, which ensure the regulation of water resources in the northeastern region of Algeria.

Therefore, the proper management of water quality in BH dam may impact positively these interlinked dam-reservoirs. In other words, the implementation of an efficient control system in BH dam can prevent the spreading of water quality problems to other dams, hence, avoiding further economic losses and more damage to the ecosystem.

In order to develop such a control system, the present chapter integrates under the same setting four objectives: (1) Analyze the variations of 22 hydrochemical parameters at BH dam over a period of 11 years (2000-2010) to identify the major factors causing its water quality deterioration. (2) Considering BH dam's two upstreams, i.e. Wadi Rhumel (WR) and Wadi Endja (WE), determine the upstream that is the most important source of water pollution. (3) Evaluate water quality for drinking, irrigation, industrial and aquatic life purposes. (4) Detect the trend of water quality in BH dam. To achieve these objectives, we use a methodological framework that combines PCA and FA, K-means clustering, CCME-WQI and Mann (1945)-Kendall (1975) test.

VI.1. Application settings

VI.1.1 Study area description

BH dam is the largest hydraulic structure built in recent decades in Algeria. It is located nearly 15 km from Mila city, in the Kebir-Rhumel watershed (**Figure VI.1**) which covers an area of approximately 8815 km^2 and is fed by two main wadis: WR and WE

(Bouaroudj et al., 2019). This dam is a vital water resource in the region, with a total storage capacity of 960 Mm^3, and intended to supply drinking water to more than two million people in six eastern provinces (Mila, Jijel, Constantine, Batna, Oum El-bouaghi and Khenchela) by 2030 and contribute to the irrigation of about 102,000 acres of agricultural land of Teleghma, Remila, Ouled Fadel and Batna. (Marouf and Remini, 2016).

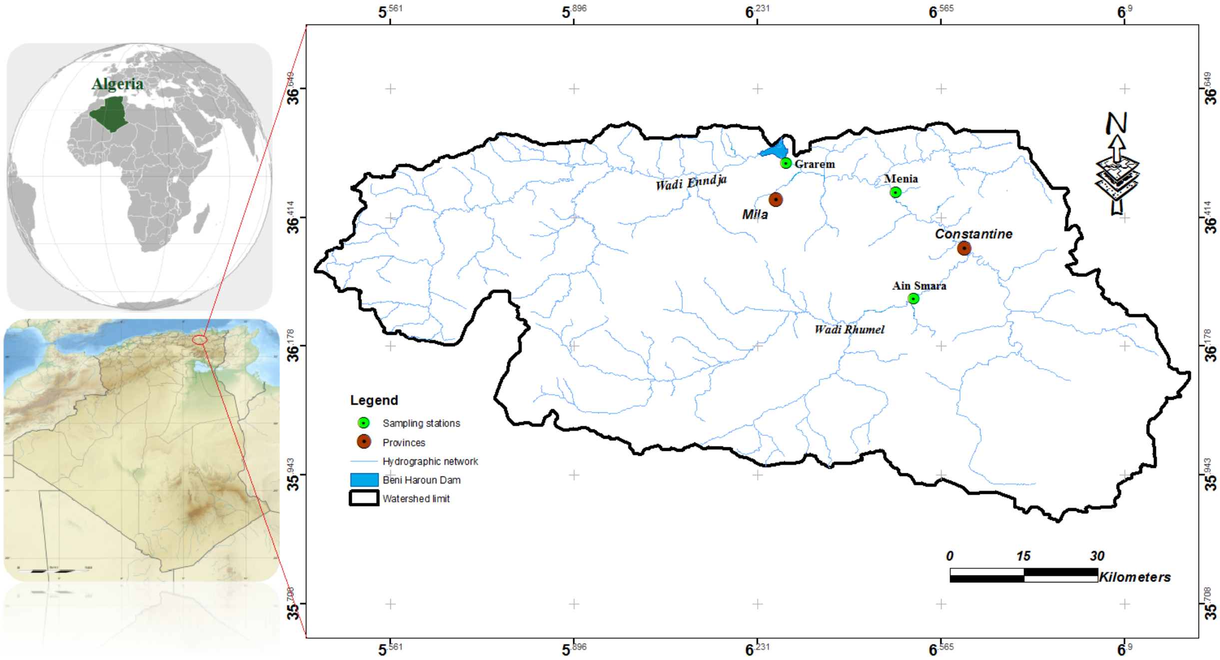

Figure VI.1. : Location of the study area

The area that hosts the dam site is a rugged relief with remarkable topographical contrasts, high mountain ranges, and deepened ravines. The rock units on site are of the type (i) Eocene marlstone which has been strongly deformed and altered, (ii) Eocene limestone bar (Ypresian) representing the support of the dam and, (iii) black Paleocene marlstone (Mebarki et al., 2008). The climate of the region is semi-arid in the south and sub-humid in the north, characterized by significant rainfall variability.

The records from BH dam meteorological station show that the average rainfall varies between 200 and 1120 mm/year. The winter season is the wettest. Hence, the study area is characterized by humid winter and dry summer. The highest monthly average temperature recorded in summer (June-September) ranges between 25 and 28°C. The lowest temperatures are observed during the winter period (December-March) with a minimum average of 9.7°C in January.

VI.1.2 Sampling sites

ANRH conducts monthly sampling campaigns for monitoring water quality parameters in many areas (dams or rivers). A data set of twenty-two physicochemical parameters has been collected over 11 years (2000 to 2010) from three different hydrochemical stations, including Ain Smara (ST1), Menia (ST2) and Grarem (ST3) stations. The last station represents the water characteristics of BH dam's lake, while the other two stations are located in WR, one of the dam's upstreams.

The measured parameters comprise water temperature (T), dissolved oxygen (DO), pH, electrical conductivity (EC), total suspended solids (TSS) and major cations and anions (Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, HCO_3^{-}, Cl^{-}, SO_4^{2-}), NO_3^{-}, NO_2^{-}, NH_4^{+}, PO_4^{3-}, COD, BOD and heavy metals (Cu, Zn, Fe and Mn). The water samples were collected, preserved, transported, and analyzed by the engineers of the ANRH using the standard method described by (Rodier et al., 2009). The ionic charge balance of each sample was within the acceptable limit of +5 %.

VI.2. Methodological framework

In order to achieve the objectives of this study, we develop the conceptual framework depicted in **Figure VI.2.**

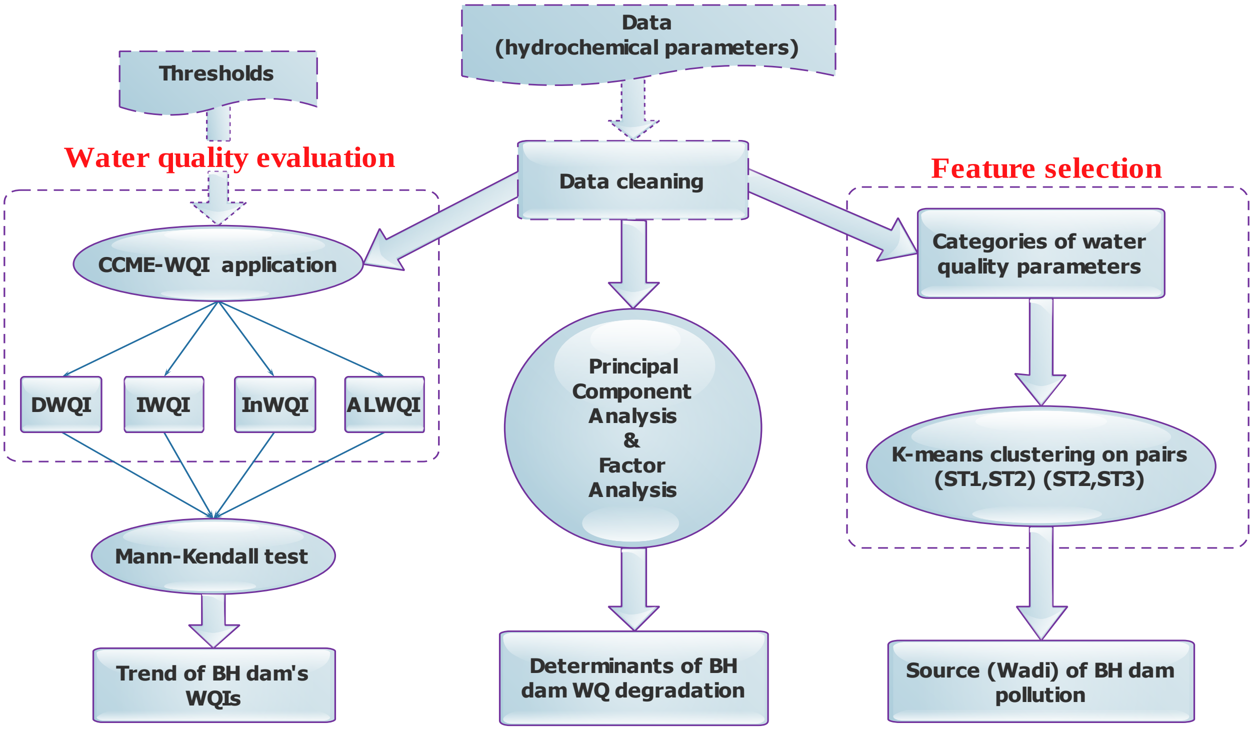

Figure VI.2. : Flowchart of the methodological framework

VI.2.1 Data treatment

Data cleaning and preprocessing is an important step to identify and resolve problems related to outliers, noise, or missing values (Zou et al., 2015). In this study, outliers are detected and removed using the whisker box (Tukey, 1977), which has the advantage of not requiring any distribution assumptions. The missing values were estimated by multiple imputations, which is known in the scientific community for giving accurate results (Benahmed and Houichi, 2018).

Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were performed to verify the suitability of PCA/FA application on the data set. KMO test is a measure of sampling adequacy that provides an index between (0 and 1) reflecting the proportion of variance among the variables (Wang et al., 2012), whereas Bartlett's sphericity test indicates whether the correlation matrix is an identity matrix, indicating that the variables are unrelated (Varol and Şen, 2008). The results of KMO and Bartlett's tests were KMO=0.78 and p=0.0001, respectively, which indicate that the application of PCA/FA is adequate. In this investigation, PCA/FA and K-means clustering were carried out on standardized data set through Z-scale transformation to avoid misclassification due to various parameter measurement units (Liu et al., 2003). All mathematical and statistical computations were conducted using XLStat 2016 (Addinsoft ®) and Statistica 12 (StatSoft, Inc. ®) software.

VI.3. Results and discussion

VI.3.1 Descriptive statistics

Summary statistics for water quality parameters measured at the three sampling stations, ST1, ST2, and ST3, over 11 years are presented in **Table VI.2.** These statistics include the sample mean *m* and standard deviation *s* (*m*±*s*), and the range (min, max). Most mean values of the parameters exceed the permissible thresholds (see, **Table I.5** and **Table I.6**) for different uses i.e., drinking, irrigation, industry and aquatic life apart from T, pH, TSS, HCO_3^-, Cu, and Mn.

Table VI.1. Statistics of the measured parameters at the 3 stations during 11 years

Parameters	Sampling Stations		
	ST1	**ST2**	**ST3**
T (°C)	16±7 (5-30)	19±7 (6-35)	19±6 (7-30)
pH	7.8±0.3 (7-8.5)	7.7±0.3 (7-8.4)	7.9±0.3 (7.3-8.5)

DO (mg/l)	7.62±1.26 (4.29-10.8)	6.2±1.58 (1.59-11)	7.37±1.89 (1.92-15)
EC (µS/cm)	1906±427 (800-2800)	1873±243 (1160-2500)	1509±448 (800-2700)
TSS (mg/l)	129±77 (18-360)	146±94 (7-470)	142±78 (17-320)
Ca^{2+} (mg/l)	165±49 (38-255)	147±37 (58-198)	112±28 (40-186)
Mg^{2+} (mg/l)	55±17 (9-94)	55±19 (21-115)	42±15 (17-85)
Na^{+} (mg/l)	144±53 19-274	149±41 (50-246)	121±41 (45-230)
K^{+} (mg/l)	6.32±3.74 (0-14)	9.56±5.59 (0-24)	6.3±4.19 (0-16)
Cl^{-} (mg/l)	230±65 (65-395)	225±58 (20-350)	172±52 (45-305)
SO4^{2-} (mg/l)	380±70 (200-550)	291±66 (146-460)	279±68 (174-462)
HCO$_3^-$ (mg/l)	292±78 (114-488)	371±107 (146-671)	256±120 (110-561)
NO$_3^-$ (mg/l)	22.88±12.96 (0-53)	9.91±7.45 (0-32)	12.52±7.98 (0-34)
NO$_2^-$ (mg/l)	0.96±0.75 (0-3.29)	1.14±0.86 (0-3.56)	0.4±0.39 (0-1.58)
NH$_4^+$ (mg/l)	1.11±0.74 (0-3.92)	7.46±5.79 (0-26)	0.31±0.40 (0-1.42)
PO$_4^{3-}$ (mg/l)	1.35±0.96 (0-4)	5.23±3.51 (0-14)	0.91±1.08 (0-4.5)
COD (mg/l)	58±25 (7-115)	74±31 (12-161)	81±27 (18-137)
BOD (mg/l)	7.93±3.72 (0.1-20)	13.07±7.45 (0.5-32.7)	10.79±6.33 (0-27.5)
Cu (mg/l)	0±0.01 (0-0.025)	0.01±0.01 (0-0.03)	0.01±0.01 (0-0.05)
Zn (mg/l)	0.01±0.01 (0-0.043)	0.03±0.03 (0-0.121)	0.01±0.02 (0-0.073)
Fe (mg/l)	0.42±0.45 (0-2.02)	0.35±0.3 (0-1.45)	0.47±0.61 (0-2.25)
Mn (mg/l)	0.08±0.08 (0-0.326)	0.09±0.07 (0-0.31)	0.06±0.05 (0-0.22)

ST1 and ST2 display high concentrations in most of the samples compared to the BH dam gauging station (ST3). These high concentrations may come mainly from domestic discharges and the chemical fertilization industry in the city of Constantine and its surroundings (Marouf and Remini, 2016). The one-way analysis of variance (ANOVA), conducted to investigate the parameters temporal variations over the seasons (winter, spring, summer, and fall), indicates that, at 5% significance level, most parameters do not show significant variations except T, Na$^+$, HCO$_3^-$, Cl$^-$, and COD, which have the highest scores in summer (dry season), whereas DO, NO$_3^-$, NO$_2^-$, and Zn record the highest scores in winter (wet season), and vice versa.

VI.3.2 Determinants of water quality variability

PCA/FA have been employed on standardized data set of 22 parameters and 105 samples [20 × 105] from BH dam station (ST3) to determine the group of parameters that influence the variability of the water quality. After the varimax rotation of PCs, only Seven VFs with eigenvalue>1 were taken into account (**Table VI.3.**), which constitutes about 67,35% of the total variance in the water quality database. The parameters loading from the retained VFs have been classified as "*Strong*", "*Moderate*" and "*Weak*" with absolute loading values >0.75, 0.75-0.50, and 0.50-0.30, respectively (Liu et al., 2003).

Table VI.3: Variances in parameter loadings explained by rotated principal components

Parameters	VF1	VF2	VF3	VF4	VF5	VF6	VF7
T	0.307	**-0.628**	-0.130	0.278	-0.050	-0.143	-0.061
pH	0.149	0.052	0.303	**0.630**	-0.103	-0.239	-0.031
DO	**-0.659**	-0.005	-0.074	-0.043	-0.079	-0.014	-0.219
EC	**0.792**	0.285	0.138	0.394	-0.050	0.021	-0.079
TSS	-0.430	-0.026	0.337	0.150	-0.330	0.122	-0.085
Ca^{2+}	0.410	0.233	-0.018	-0.071	**0.513**	0.232	-0.071
Mg^{2+}	0.220	0.087	-0.050	**0.752**	0.121	0.062	0.142
Na^{+}	**0.856**	0.038	0.046	0.218	0.022	0.058	-0.071
K^{+}	**0.691**	0.343	-0.071	0.190	-0.267	-0.126	0.034
Cl^{-}	**0.816**	-0.062	0.133	0.221	0.020	0.066	-0.004
SO_4^{2-}	0.448	0.124	0.111	**0.611**	0.341	0.010	-0.041
HCO_3^{-}	**0.700**	**0.551**	0.154	0.127	-0.050	0.082	-0.096
NO_3^{-}	0.303	**0.581**	0.503	0.023	0.054	-0.140	-0.037
NO_2^{-}	0.143	**0.586**	-0.083	0.082	0.355	-0.122	-0.028
NH_4^{+}	0.153	**0.703**	-0.002	0.359	0.061	0.114	0.120
PO_4^{3-}	0.479	**0.541**	-0.125	0.318	0.175	-0.030	-0.149
COD	0.205	-0.109	-0.119	-0.160	**-0.727**	0.000	-0.058
BOD	0.198	-0.116	-0.366	-0.185	0.037	-0.330	**0.529**
Cu	-0.052	0.089	0.184	0.169	0.009	0.146	**0.813**
Zn	0.067	0.017	0.028	-0.060	0.052	**0.869**	0.046
Fe	0.279	0.465	-0.187	0.463	-0.153	0.346	0.054
Mn	0.195	-0.022	**0.798**	0.055	0.101	0.033	0.116
Eigenvalue	6.62	2.04	1.50	1.26	1.20	1.15	1.05
Total variance %	30.08	9.26	6.81	5.72	5.46	5.25	4.77
Cumulative %	30.08	39.34	46.15	51.87	57.33	62.58	67.35

The first VF1 explains 30.08% of the entire data set, has strong positive loadings on EC, Na^+, and Cl^-, moderate loadings on K^+ and HCO_3^-, and moderately negative loading on DO. This factor can be interpreted as the salinity component of the reservoir's water, which contains naturally dissolved ions from soil erosion, rainfall, water-rock interaction, and runoff. Increasing dissolved ions will lead to increasing EC (Hamil et al., 2018). The DO is a good indicator of water pollution because the vital functions of aquatic life, such as the respiration of organisms and self-purification, will be negatively influenced by low levels of DO, particularly in the hot season (summer).

VF2 accounts for 9.25% of the total variance, has moderate positive loadings on NH_4^+, NO_2^-, NO_3^-, and PO_4^{3-} and a moderate negative loading on T. The negative association of T maybe because the nutrients loadings occur more intensely in winter, associated with rainfall-runoff. This factor represents the contribution of non-point source pollution from agricultural land use since farmers in this region apply nitrogen and phosphate fertilizers, which are subsequently leached into the dam's lake by runoff (Shrestha and Kazama, 2007). It should be noted that the water body enriched with these nutrients accelerates the eutrophication phenomenon and causes excessive algal growth.

The remaining factors, i.e., VF3,4,5,6 and 7 constitute respectively 6.81%, 5.72%, 5.46% 5.25% and 4.77% of the total variance, which has strong positive loadings on heavy metals (Mn, Zn and Cu), and moderate loadings on other inorganic salts (Ca^{2+}, Mg^{2+} and SO_4^{2-}), and BOD and a moderately negative loading on COD. These VFs indicate sources of hardness, organic pollution and toxic substances from stream inflows, point sources such as sewage treatment plant discharges, municipal wastewater and industrial effluents.

VI.3.3 Similarity among sampling stations

The purpose of using K-means clustering is to determine similarities and dissimilarities between BH dam and its upstreams in terms of water quality properties. Note that BH dam is considered a confluence of the two main wadis i.e., WR and WE in the Kebir-Rhumel watershed. Moreover, it is noteworthy that data are only available for the water physicochemical parameters of WR, which comprises ST1 and ST2, but there is no feedback about WE water quality.

Therefore, the use of an unsupervised machine learning algorithm, such as K-means clustering, on the data set of all monitoring stations, i.e. ST1, ST2 and ST3, will be useful to extract meaningful information.

K-means algorithm has been applied to the water quality parameters of pairs of consecutive stations, i.e., (ST1, ST2) and (ST2, ST3) to assess similarities among the stations. In this context, the parameters of each pair were categorized into five classes, namely: Physicochemical parameters group (T, pH, DO and TSS), Major ions group (Ca^{2+}, Mg^{2+}, Na^+, K^+, Cl^-, SO_4^{2-} and $HCO3^-$), Chemical nutrients group (NO_3^-, NO_2^-, NH_4^+ and PO_4^{3-}), Organic pollution group (BOD and COD) and Heavy metals group (Cu, Zn, Fe and Mn). K-means plots were obtained using RStudio (2019) software.

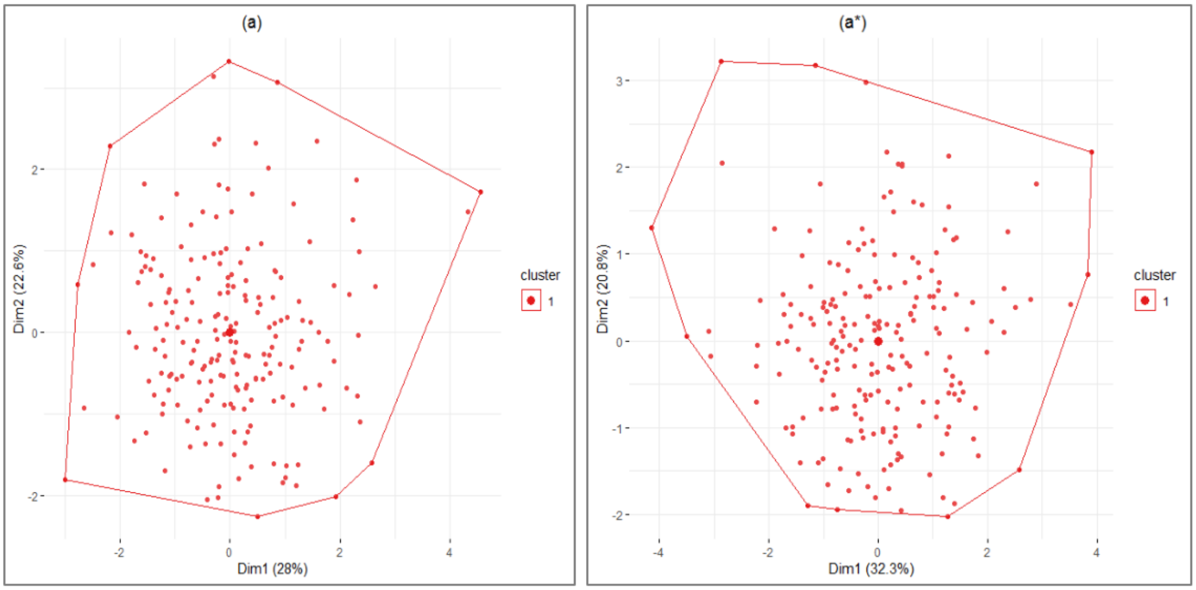

Figure VI.3: 2-D plot of the physicochemical parameters' group using K-means algorithm. (a) (ST1, ST2) and (a*) (ST2, ST3)

As shown in **Figure VI.3.**, data points of the first class (Physicochemical parameters) have been grouped into one cluster for the two scenarios (ST1, ST2) and (ST2, ST3), whereas the representation of these scenarios in 2D is explained by 50.6% and 53.1% of the total variance, respectively. These results suggest that all sampling stations have the same Physicochemical water quality features.

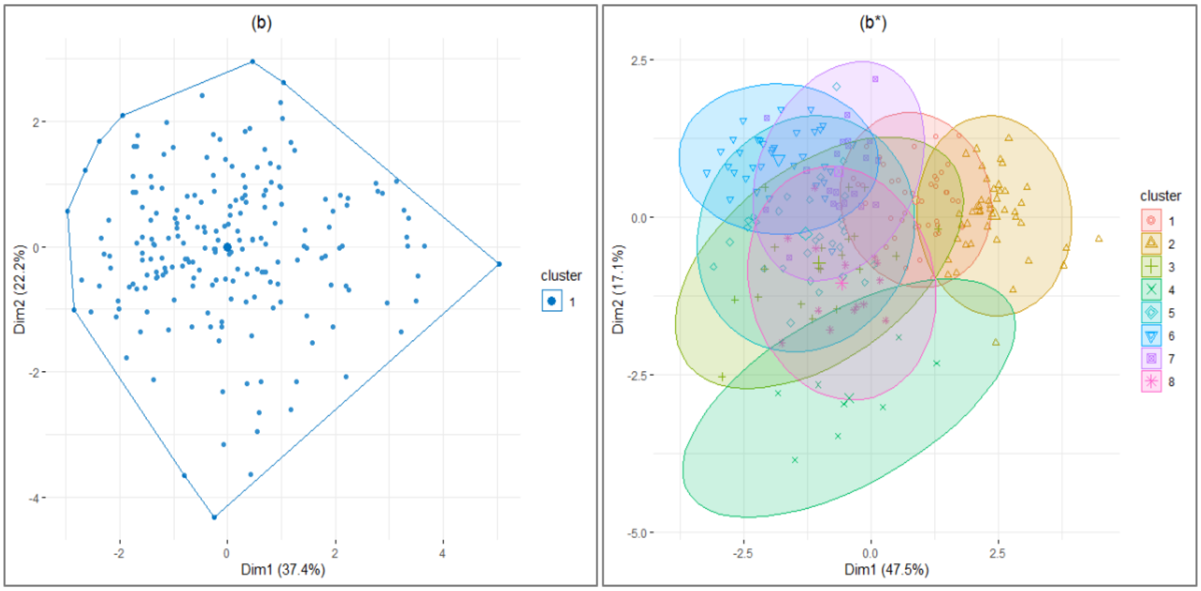

Figure VI.4: 2-D plot of the major ions' group using K-means algorithm. (b) (ST1, ST2) and (b*) (ST2, ST3)

The application of K-means approach on the class of major ions (**Figure VI.4**) indicates that ST1 and ST2 have the same water quality characteristics (one cluster). Meanwhile, data points of the pair (ST2, ST3) have been divided into 8 clusters. Such clear dissimilarity between ST2 and ST3 can be assigned to the variation in water quality of ST3 due, perhaps, to inputs from another water source, such as WE.

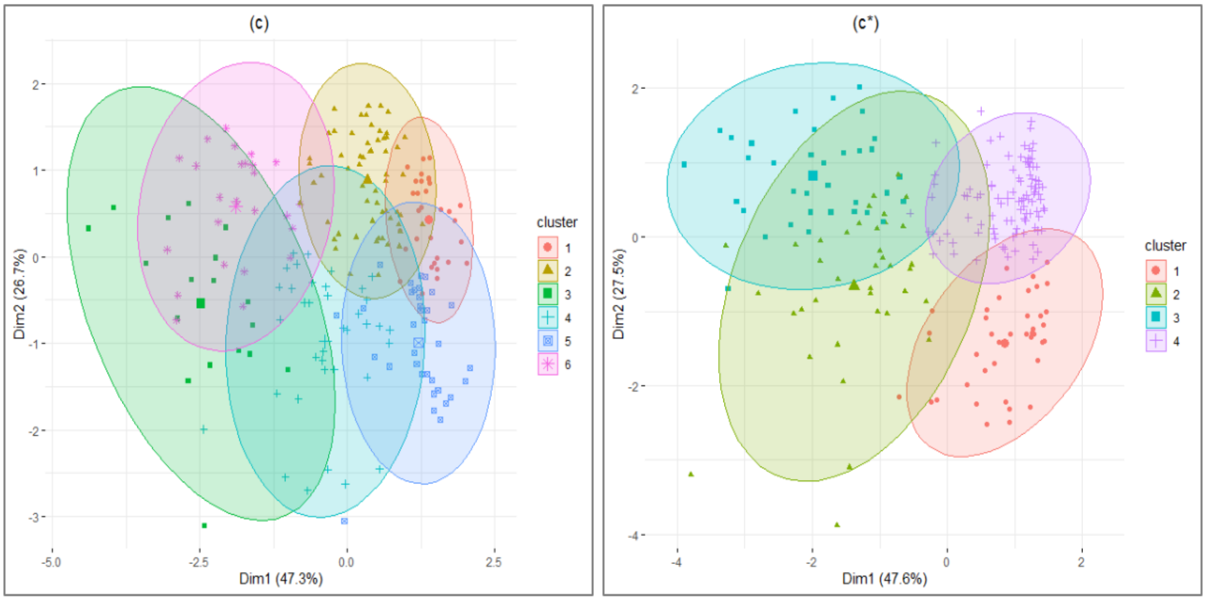

Figure VI.5: 2-D plot of the chemical nutrients' group using K-means algorithm. (c) (ST1, ST2) and (c*) (ST2, ST3)

According to **Figure VI.5**, the concentrations of chemical nutrients in the pairs (ST1, ST2) and (ST2, ST3) are split into 6 and 4 different clusters, respectively, meaning that there are no common characteristics among the three sites.

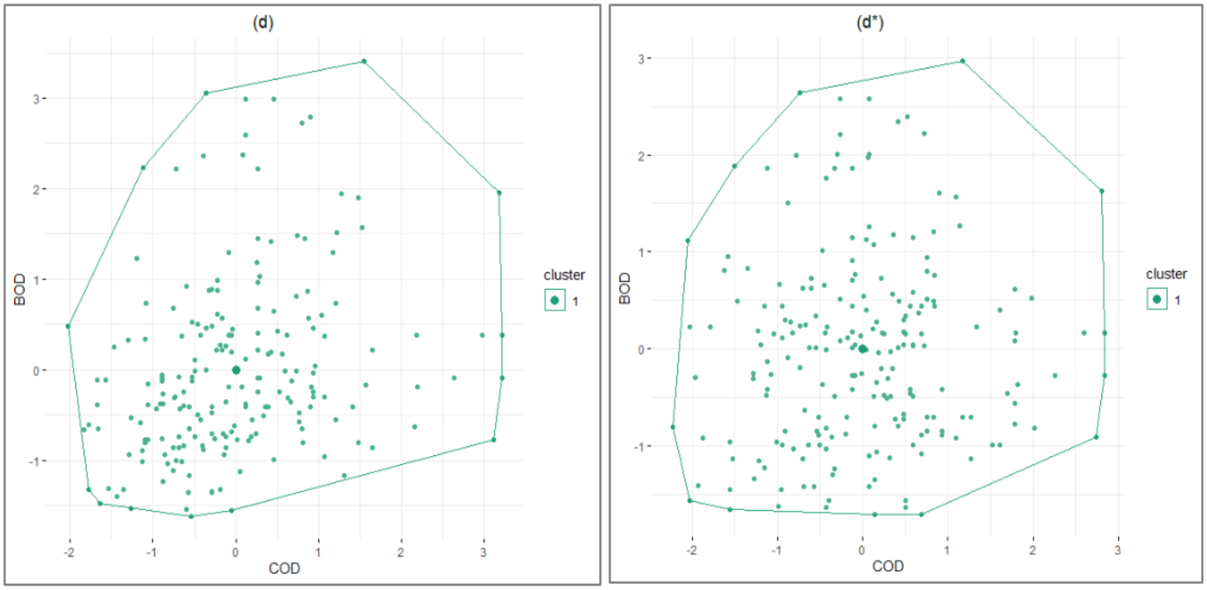

Figure VI.6: Scatter plot of BOD and COD parameters (organic pollution group) using K-means algorithm. (d) (ST1, ST2) and (d*) (ST2, ST3)

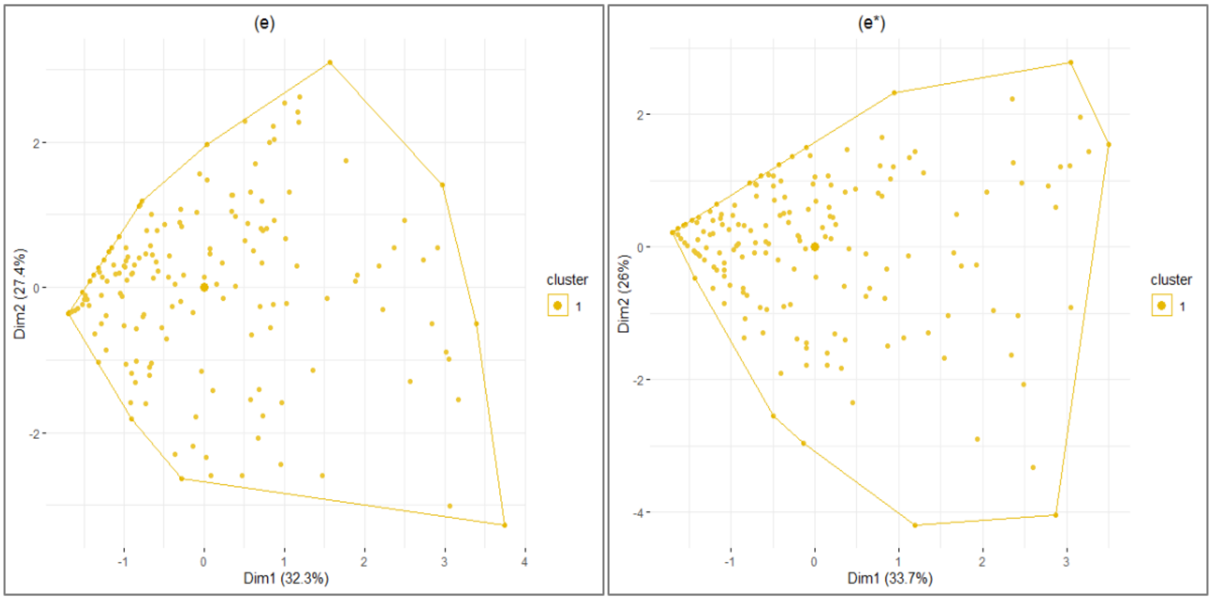

Figure VI.7: 2-D plot of the Heavy metals group using K-means algorithm. (e) (ST1, ST2) and (e*) (ST2, ST3)

Based on **Figures VI.6** and **VI.7**, the data sets of organic pollution and heavy metals are clustered into one single cluster in the two scenarios (**d**, **d***) and (**e**, **e***), which is similar to the results of the physicochemical parameters, suggesting that the stations have the same water quality characteristics.

The results of K-means clustering on several groups of water quality parameters for the paired stations (ST1, ST2) and (ST2, ST3) obviously indicate that the water quality of BH dam is susceptible to organic and heavy metals pollution in the first degree. These undesirable substances emanate from industrial and domestic point-source discharges through WR.

VI.3.4 Water quality evaluation

CCME WQI was used herein to assess the overall water quality of BH dam and its upstream WR with respect to the national and international guidelines (see, **Table I.5** and **Table I.6**) for drinking, irrigation, industry and aquatic life purposes. The WQIs have been calculated for the 03 monitoring sites using formula (**IV.11**) and the results are summarized in **Table VI.4**.

Table VI.4: CCME WQIs scores of (ST1), (ST2) and (ST3) over 11 years

Year	Water Quality Indices											
	DWQI			IWQI			InWQI			ALWQI		
	ST1	ST2	ST3	ST1	ST2	ST3	ST1	ST2	ST3	ST1	ST2	ST3
2000	18	17	20	40	31	37	64	44	67	34	29	65
2001	26	34	17	50	48	45	75	80	72	47	50	59
2002	26	18	14	39	27	29	44	32	34	36	28	28
2003	28	33	23	38	55	36	45	79	35	41	60	42
2004	23	32	20	55	56	33	77	78	34	69	53	36
2005	39	31	43	57	51	60	76	72	74	70	65	75
2006	18	17	47	42	32	66	45	40	87	35	34	91
2007	35	27	52	44	46	67	73	76	87	66	57	83
2008	17	33	48	41	57	71	45	79	88	35	59	83
2009	36	41	54	48	54	70	51	80	88	49	65	90
2010	49	23	64	55	35	72	77	42	100	84	37	100
MIN	***17***	***17***	***14***	***38***	***27***	***29***	***44***	***32***	***34***	***34***	***28***	***28***
MAX	***49***	***41***	***64***	***57***	***57***	***72***	***77***	***80***	***100***	***84***	***65***	***100***
Mean	***14***	***15***	***17***	***37***	***31***	***40***	***44***	***39***	***42***	***27***	***29***	***32***

The lowest values of WQIs are recorded between 2000 and 2003, while the highest are observed in 2009 and 2010. Station S2 has the lowest WQIs for DWQI, IWQI, InWQI and ALWQI, with values 17, 27, 32 and 28, respectively, while S3 has the highest values of 64, 72, 100 and 100, respectively. According to the overall mean values of the WQI (**Table VI.4**), the water in all three stations is of poor quality, with as a preferential setting ST3->ST1->ST2.

In the light of these results, three key points emerge: (i) Stations ST1 and ST2 in the Constantine region are heavily contaminated with pollutants due to intensive industrial activity. (ii) Water quality of ST3, though poor, is comparatively the best owing to fewer contamination levels due, probably, to the huge capacity of BH dam and the diluting effect of WE (Müller et al., 2008), or, perhaps, the natural process of self-purification at WR level, which recovers its background state after traveling a certain distance prior to reaching the downstream. The latter natural phenomenon contributes to improving water quality and reducing the amount of pollutants through multiple mechanisms of aquatic ecosystems (González et al., 2014; Wei et al., 2009). (iii) WE is less polluted than WR because WE basin is characterized by relatively high precipitation (700 mm/year) and mountainous topography, compared to WR.

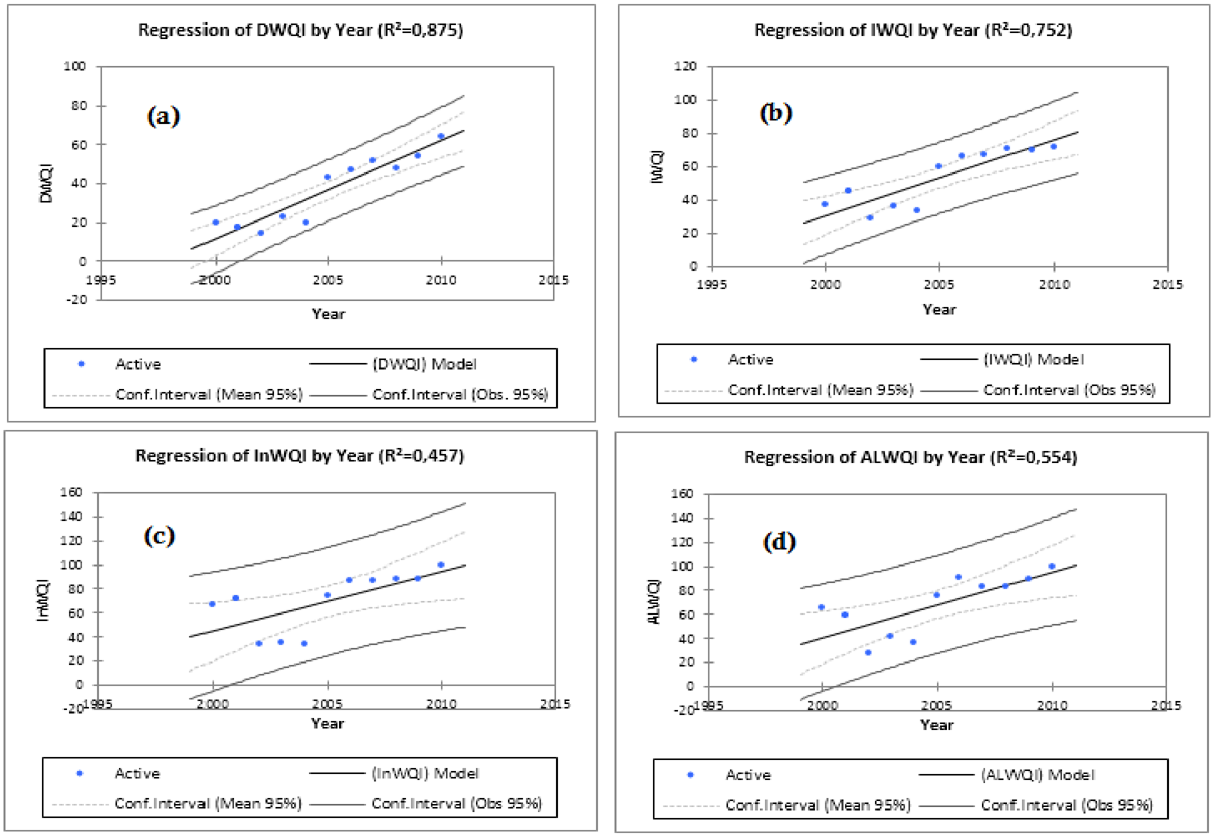

Figure VI.8: Temporal variations of all CCME WQIs values for BH dam (ST3) and their regression trends. a: Drinking. b: Irrigation. c: Industry. d: Aquatic Life.

On the other hand, the infiltration properties in the WR basin suggest that its soil is more permeable than WE basin (Marouf, 2012). We also observed that the best value of the WQIs in the BH reservoir (ST3) was in 2010, certainly as a result of operating the Sidi Merouane wastewater treatment plant in 2009, with a treatment capacity of 20657

m^3/day (Heddam et al., 2016). The temporal variations of WQIs of BH dam for different uses are shown in **Figure VI.8.**

Using the Ordinary Least Square (OLS) method, a positive trend is observed for all WQIs during 2000-2010, indicating an improvement in water quality, which may result from (i) The BH dam impoundment procedure, started in 2003, with the water volume reaching 128 hM^3 in March 2005. (ii) Connecting the sewerage networks of the urban cities of El Khroub, Ali Mendjli, Ain Smara and Békira (Hamma Bouziane) to the main collectors that converge towards the WWTP of Constantine. (iii) The implementation of the environmental fiscalization policy reinforces the "polluter pays" principle penalizing for activities that are potentially polluting or hazardous for the environment. (iv) Developing a watershed protection system through reforestation works (cypress, poplar, ash, cork oak..., fruit trees) and torrential correction along ravines that are subject to intense erosion (Mebarki, 2005).

The results of the Mann-Kendall test presented in **Table VI.5** confirm the relevance of applying the OLS method, where all null hypotheses H_0 are rejected, indicating a trend in the data.

Table VI.5: Mann-Kendall Test Results for ST3 WQIs

	Station 3			
	DWQI	IWQI	InWQI	ALWQI
Kendall's tau	0.807	0.709	0.711	0.587
S	44	39	38	32
Variance of S	164	0	162	164
p value	0.0006	0.002	0.003	0.012
Alpha (α)	0.05	0.05	0.05	0.05
Test	Reject H_0	Reject H_0	Reject H_0	Reject H_0

Given the high importance that BH dam occupies in the eastern region of Algeria, several studies have been carried out to explore the main risks facing the sustainability of this strategic megaproject. Remini and Toumi (2017), and Kateb *et al.* (2020) have examined the problem of the silting phenomenon that threatens to reduce the dam's storage capacity. They found a volume of 118 million m^3 of mud deposited during ten years of operation and the total soil erosion rate of the watershed is estimated to 3944.835 tons/km^2/year.

Many important studies on water quality assessment have been conducted in the present study area, most notably, Marouf and Remini (2016) who analyzed the evolution of different physicochemical, organic and bacteriological parameters in the Kebir Rhumel watershed and BH dam reservoir over ten years (1984-2004) and five years (2007-2011), respectively. Their findings revealed that excessive concentrations of undesirable substances such as nitrate (NO_3^-) and phosphate (PO_4^{3-}) are the main factors causing the algal blooms and eutrophication, which emerged in the form of green-colored water at the edge of BH dam and Ain Smara station. In addition, noticeable concentrations of sulfate (SO_4^{2-}) have been recorded in various water samples, as well as organic, chemical and microbiological contamination due to the high levels of BOD_5, COD, dissolved and saturated oxygen released by urban and industrial discharges. Interestingly, the results of (Marouf and Remini, 2016) investigation appear considerably consistent with our findings.

In a subsequent study, Kherief Nacereddine *et al.* (2018) examined the dynamics of thirteen physicochemical and biotic parameters, as well as their effect on the development of the micro-algal phytoplankton population at five different sites located on the lake of BH dam, over a twelve-month period in 2015. Their results showed that the nutrient contents are not yet alarming but the situation is likely to worsen with the various inputs of pollution that are constantly increasing.

On the heels of (Kherief Nacereddine et al., 2018) study, Djeddi *et al.* (2018) assessed the degree of pollution associated to three heavy metals i.e., Cu, Zn and Pb at five monitoring stations in the surface sediments of BH dam. The results of this study showed that the spatial distribution of heavy metal contents of Cu and Zn were at natural levels, but Pb contamination is widespread and affects all the stations.

Recently, Bouaroudj *et al.* (2019) investigated the impact of BH dam's water on soil characteristics of six irrigated areas by measuring thirteen related water quality parameters at eight sites along with the water indices. They concluded that the water from BH dam can be used for irrigation purposes with certain precautions and suggested the need for adequate protection measures with relevant guidelines for water-soil parameters so that to minimize the adverse effects of irrigation water on agricultural areas.

Conclusion

The application of different techniques to assess the spatio-temporal water quality of BH dam and its upstream have revealed valuable results. PCA/FA, showed that the water quality of BH dam is influenced by two major pollution factors: (i) natural processes and (ii) anthropogenic non-point source pollution. The hyper-salination of water resulting from dissolved minerals of weathering and runoff can lead to an increase in electrical conductivity and threaten aquatic life. On the other hand, excessive concentrations of NO_3^-, NO_2^-, NH_4^+ and PO_4^{3-} are related mostly to non-point source anthropogenic pollution from agricultural fertilization and represent the principle factor of eutrophication. This latter can be the cause of the mortality of living organisms. In addition, organic pollution and heavy metals, which are also of the anthropogenic source (municipal and industrial point-source discharges), contribute considerably to the deterioration of water quality.

The K-means algorithm shows a clear similarity in water quality between BH dam and its upstream WR. WR is the main pollution source of the dam's water in terms of Physicochemical, Organic and Heavy metals contamination.

CCME-WQI has been applied and, based on national and universal guidelines, BH dam’s water quality has been classified as "poor" for drinking, irrigation, industrial and aquatic life purposes over 11 years (2000-2010). However, the most striking finding of the study is definitely the increasing trend of the WQI over time, which is rather promising.

The findings of this study will be of great support to decision-makers in the water resources sector over many managerial levels, including (1) the identification of the factors affecting the water quality of BH dam, (2) the estimation of the costs pertaining to water treatment processes based on the WQI spatial and temporal variations, and (3) the mitigation of the impacts of anthropogenic pollution on the environment by implementing firm provisions on those who fail to comply with regulations and sanitation standards.

Conclusions

Water has always been the most vital resource on the earth's planet. People should be therefore responsible for its consequences use, and deterioration. The work presented in this thesis is mainly devoted to the study of the surface water quality of most Algerian dams located in the northern part, using sophisticated techniques and approaches that allow, on the one hand, to represent the overall water quality of the studied sites in easy and understandable way employing the score of Water Quality Index concept, and, on the other hand, to be a very effective tool in ranking and prioritizing the most deteriorated dams. Furthermore, the use of these approaches is fully reliable in specifying the factors that may be causing pollution.

The first part of such thesis is dedicated to giving an overview of the existing quantity of water resources in Algeria along with needed measures to face the perceived deficit. Also, the types of aquatic pollutants and parameters that play a key role in the degradation of water quality are identified. Given the wide range of methods used for assessing water quality in the literature, the second chapter has been directed at this task.

After that, the study area chapter describes its location, topography, precipitation, etc. Where, this area occupies approximately the whole North of Algeria that is limited by the coordinates of longitudes 2°13'48 "W and 8°40'12 "E and latitudes 37°7'12 "N and 32°44'24 "S. Its total area is about 225 105 Km^2 includes the Tellian Atlas in the North and the Saharan Atlas in the South, which are two large massifs in parallel, approaching each other to the East and between which are inserted vast plains and high plateaus. The average rainfall varies according to an East-West and North-South gradient. In the subsequent chapter, the used approaches in two contributions have been extensively described including Data DEA-WQI, CCME-WQI, K-means clustering algorithm, PCA/FA, and OLS techniques.

In the first-fold contribution, we have proposed a new index based on DEA model to evaluate the water quality of 47 Algerian 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 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$\succ$CSM$\succ$CZ$\succ$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 second-fold contribution, the remaining techniques as CCME-WQI, K-meas algorithm, PCA/FA and OLS have been applied to assess the spatiotemporal water quality of Beni Haroun (BH) dam and its upstream. PCA/FA, showed that the water quality of BH dam is influenced by two major pollution factors: (i) natural processes and (ii) anthropogenic non-point source pollution. On the other hand, excessive concentrations of NO_3^-, NO_2^-, NH_4^+ and PO_4^{3-} are related mostly to non-point source anthropogenic pollution from agricultural fertilization and represent the principle factor of eutrophication. In addition, organic pollution and heavy metals, which are also of the anthropogenic source (municipal and industrial point-source discharges), contribute considerably to the deterioration of water quality. The K-means algorithm shows a clear similarity in water quality between BH dam and its upstream WR. WR is the main pollution source of the dam's water in terms of Physicochemical, Organic and Heavy metals contamination. CCME-WQI has been applied and, based on national and universal guidelines, BH dam’s water quality has been classified as "poor" for drinking, irrigation, industrial and aquatic life purposes over 11 years (2000-2010). However, the most striking finding of the study is definitely the increasing trend of the WQI over time, which is rather promising.

Finally, we suggest some **recommendations** and **future works** that we consider necessary to improve the results of the various works carried out in the framework of this thesis and which are summarized in the following points:

- ✓ *Enhancing the performance of the current monitoring system by setting up more additional gauging points of water quality.*

- ✓ *Implementing more sophisticated data science tools, such as artificial intelligence (AI) to predict water quality parameters that require costly measurements.*

- ✓ *Future research could explore the application of DEA models with missing data to allow the inclusion of all hydrochemical parameters in the development of the WQI, even if complete data are only available for a few dams in the study sample.*

- ✓ *Further DEA models may also be explored to refine the ranking of dams, such as DEA bootstrap, DEA cross-efficiency, and DEA super-efficiency, which are commonly adopted to overcome the multiple occurrences of effectiveness.*

References

Abbasi, T., Abbasi, S.A., 2012. Water quality indices. Elsevier.

Agence de Bassin Hydrographique Oranais Chott Chergui (ABHOCC), 2006a. Hydraulic cadastre, Macta Basin. Synthesis Report. Ministry of Water Resources, Algiers (In French).

Agence de Bassin Hydrographique Oranais Chott Chergui (ABHOCC), 2006b. Hydraulic cadastre, Tafna Basin. Synthesis Report. Ministry of Water Resources, Algiers (In French).

Agence Nationale des Resources Hydrauliques (ANRH), 2009. Annu Hydrol de l'Algérie (Alger, Hydrological Yearbook of Algeria). Water Resources Ministry.

Agency Hydrographic Basin Sahara, 2005. Sub regional report on water resources development in north Africa.

Al-Mezeini, N.K., Oukil, A., Al-Ismaili, A.M., 2020. Investigating the efficiency of greenhouse production in Oman: A two-stage approach based on Data Envelopment Analysis and double bootstrapping. Journal of Cleaner Production 247, 119160. https://doi.org/10.1016/j.jclepro.2019.119160.

Algerian Water Authority: Algerienne des Eaux (ADE), 2011.

Amiri, V., Rezaei, M., Sohrabi, N., 2014. Groundwater quality assessment using entropy weighted water quality index (EWQI) in Lenjanat, Iran. Environmental Earth Sciences 72, 3479-3490. https://doi.org/10.1007/s12665-014-3255-0.

ANRH, 1993. Carte pluviométrique pour l'Algérie du Nord, Agence Nationale des Ressources Hydriques.

ANRH, 2009. Réseau de surveillance de la qualité des eaux superficielles, Agence Nationale des ressources hydrauliuqes.

ANRH, 2016. Agence nationale des ressources hydrauliques (ANRH) (Algérie).

Ay, M., Kisi, O., 2014. Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques. Journal of Hydrology 511, 279-289. https://doi.org/10.1016/j.jhydrol.2014.01.054.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science 30, 1078-1092. http://doi.org/10.1287/mnsc.30.9.1078.

Beamonte, E., Bermúdez, J.D., Casino, A., Veres, E., 2005. A global stochastic index for water quality: The case of the river Turia in Spain. Journal of Agricultural, Biological, and Environmental Statistics 10, 424. https://doi.org/10.1198/108571105x80987.

Belkhiri, L., Boudoukha, A., Mouni, L., 2011. A multivariate statistical analysis of groundwater chemistry data. International journal of environmental research (IJER) 5, 537-544.

Belkhiri, L., Boudoukha, A., Mouni, L., Baouz, T., 2010a. Application of multivariate statistical methods and inverse geochemical modeling for characterization of groundwater — A case study: Ain Azel plain (Algeria). Geoderma 159, 390-398. https://doi.org/10.1016/j.geoderma.2010.08.016.

Belkhiri, L., Boudoukha, A., Mouni, L., Baouz, T., 2010b. Multivariate statistical characterization of groundwater quality in Ain Azel plain, Algeria. African Journal of Environmental Science and Technology 4, 526-534.

Belkhiri, L., Narany, T.S., 2015. Using Multivariate Statistical Analysis, Geostatistical Techniques and Structural Equation Modeling to Identify Spatial Variability of Groundwater Quality. Water Resources Management 29, 2073-2089. https://doi.org/10.1007/s11269-015-0929-7.

Benahmed, L., Houichi, L., 2018. The effect of simple imputations based on four variants of PCA methods on the quantiles of annual rainfall data. Environmental monitoring and assessment 190, 569. https://doi.org/10.1007/s10661-018-6913-y.

Bencer, S., Boudoukha, A., Mouni, L., 2016. Multivariate statistical analysis of the groundwater of Ain Djacer area (Eastern of Algeria). Arabian Journal of Geosciences 9, 248. https://doi.org/10.1007/s12517-015-2277-6.

Bhargava, S.D., 1983. Use of water quality index for river classification and zoning of Ganga river. Environmental Pollution Series B, Chemical and Physical 6, 51-67. https://doi.org/10.1016/0143-148X(83)90029-0.

Bhattacharya, S., Gupta, A.B., Gupta, A., Pandey, A., 2018. Introduction to Water Remediation: Importance and Methods, in: Bhattacharya, S., Gupta, A.B., Gupta, A., Pandey, A. (Eds.), Water Remediation. Springer Singapore, Singapore, pp. 3-8.

Bouabdelli, S., Meddi, M., Zeroual, A., Alkama, R., 2020. Hydrological drought risk recurrence under climate change in the karst area of Northwestern Algeria. Journal of Water and Climate Change. https://doi.org/10.2166/wcc.2020.207.

Bouaroudj, S., Menad, A., Bounamous, A., Ali-Khodja, H., Gherib, A., Weigel, D.E., Chenchouni, H., 2019. Assessment of water quality at the largest dam in Algeria (Beni Haroun Dam) and effects of irrigation on soil characteristics of agricultural lands. Chemosphere 219, 76-88. https://doi.org/10.1016/j.chemosphere.2018.11.193.

Bouchard, C., Abi-Zeid, I., Beauchamp, N., Lamontagne, L., Desrosiers, J., Rodriguez, M., 2010. Multicriteria decision analysis for the selection of a small drinking water treatment system. Journal of Water Supply: Research and Technology-Aqua 59, 230-242. https://doi.org/10.2166/aqua.2010.071.

Bouderbala, A., Remini, B., Saaed Hamoudi, A., Pulido-Bosch, A., 2016. Application of Multivariate Statistical Techniques for Characterization of Groundwater Quality in the Coastal Aquifer of Nador, Tipaza (Algeria). Acta Geophysica 64, 670-693. https://doi.org/10.1515/acgeo-2016-0027.

Bouguerne, A., Boudoukha, A., Benkhaled, A., Mebarkia, A.-H., 2017. Assessment of surface water quality of Ain Zada dam (Algeria) using multivariate statistical techniques. International Journal of River Basin Management 15, 133-143. https://doi.org/10.1080/15715124.2016.1215325.

Bouslah, S., 2018. Etude de la qualite des eaux stockees a l'amont et les eaux d'infiltration a l'aval des barrages en remblai en Algerie, Hydraulique. Université Badji Mokhtar-Annaba, p. 221.

Bouslah, S., Djemili, L., Houichi, L., 2017. Water quality index assessment of Koudiat Medouar Reservoir, northeast Algeria using weighted arithmetic index method. Journal of water and land development 35, 221-228.

Boyd, C.E., 2015. Dissolved Solids, Water Quality: An Introduction. Springer International Publishing, Cham, pp. 71-100.

Brown, R.M., McClelland, N.I., Deininger, R.A., Tozer, R.G., 1970. A WATER QUALITY INDEX- DO WE DARE.

Canadian Council Ministers of Environment (CCME), 2001. Canadian water quality guidelines for the protection of aquatic life: CCME Water Quality Index 1.0, User's manual, Canadian Environmental Quality Guidelines. Canadian Council of Ministers of the Environment, Winnipeg, Manitoba, p. 5.

Chapman, D.V., 1996. Water quality assessments: a guide to the use of biota, sediments and water in environmental monitoring. CRC Press.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European journal of operational research 2, 429-444.

Commission of European Committees (CEC), 1978. Council Directive of 18 July 1978 on the quality of fresh waters needing protection or improvement in order to support fish life, (78/659/EEC). Official J L/222:1–10.

Cook, W.D., Tone, K., Zhu, J., 2014. Data envelopment analysis: Prior to choosing a model. Omega 44, 1-4. https://doi.org/10.1016/j.omega.2013.09.004.

Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Handbook on data envelopment analysis. Springer Science & Business Media.

Cox, B., 2003. A review of dissolved oxygen modelling techniques for lowland rivers. Science of The Total Environment 314, 303-334.

Cude, C.G., 2001. Oregon water quality index a tool for evaluating water quality management effectiveness. JAWRA Journal of the American Water Resources Association 37, 125-137. https://doi.org/10.1111/j.1752-1688.2001.tb05480.x.

Davies, D.L., Bouldin, D.W., 1979. A Cluster Separation Measure. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-1, 224-227. https://doi.org/10.1109/tpami.1979.4766909.

Department of Water Affairs and Forestry (DWAF), 1996. South African Water Quality Guidelines, 2nd ed. ed. Department of Water Affairs and Forestry, Pretoria, South Africa.

Dinius, S.H., 1972. Social accounting system for evaluating water resources. Water Resources Research 8, 1159-1177. http://doi.org/10.1029/WR008i005p01159.

Dinius, S.H., 1987. Design of an index of water quality. JAWRA Journal of the American Water Resources Association 23, 833-843. https://doi.org/10.1111/j.1752-1688.1987.tb02959.x.

Djeddi, H., Kherief Nacereddine, S., Keddari, D., Afri-Mehennaoui, F.-Z., 2018. Content of Trace Metallic Elements Cu, Zn and Pb Sediments of the Béni Haroun Dam (North-East Algeria). European Scientific Journal, ESJ 14, 269. http://doi.org/10.19044/esj.2018.v14n15p269 (in French).

Djelita, B., Bouzid-Lagha, S., NEHAR, K.C., 2016. Spatial and Temporal Patterns of the Water Quality in the Hammam Boughrara Reservoir in Algeria, in: Grammelis, P. (Ed.), Energy, Transportation and Global Warming. Springer International Publishing, Cham, pp. 635-653.

Drought management strategy in Algeria, 2014. Regional workshop for the Near East and North Africa.

Drouiche, N., Ghaffour, N., Naceur, M.W., Lounici, H., Drouiche, M., 2012. Towards sustainable water management in Algeria. Desalination and Water Treatment 50, 272-284. https://doi.org/10.1080/19443994.2012.719477.

Dunn, J.C., 1974. Well-Separated Clusters and Optimal Fuzzy Partitions. Journal of Cybernetics 4, 95-104. https://doi.org/10.1080/01969727408546059.

ESRI, 1990. Understanding GIS the arc/info method. Environmental Systems Research Institute, Redlands, CA, USA.

European Union, 2014. Consultation on the quality of drinking water in the EC. https://ec.europa.eu/environment/consultations/water_drink_en.htm.

Ewaid, S.H., 2018. Irrigation water quality of Al-Gharraf Canal, south of Iraq, J. Phys. Conf. Ser, p. 012006.

Farzadkia, M., Djahed, B., Shahsavani, E., Poureshg, Y., 2015. Spatio-temporal evaluation of Yamchi Dam basin water quality using Canadian water quality index. Environmental monitoring and assessment 187, 168. https://doi.org/10.1007/s10661-015-4379-8.

Food and Agriculture Organization (FAO), 1994. Water quality for agriculture, p. 174.

Food And Agriculture Organization Of The United Nations (FAO), 2002. Human Vitamin and Mineral Requirements online http://www.fao.org/3/Y2809E/y2809e0h.htm. Accessed 24/10/2020.

Gaagai, A., 2017. Etude de l'évolution de la qualité des eaux du barrage de Babar (Sud-Est Algérien) et l'impact de la rupture de la digue sur l'environnement. Université de Batna 2.

Gaujou, S., 1995. Pollution des milieux aquatiques (aide mémoire) 2éme édition, Ed. Lavoisier, Cachan Cedex.

Ghodbane, M., Boudoukha, A., Benaabidate, L., 2016. Hydrochemical and statistical characterization of groundwater in the Chemora area, Northeastern Algeria.

Desalination and Water Treatment 57, 14858-14868. https://doi.org/10.1080/19443994.2015.1067924.

González, S.O., Almeida, C.A., Calderón, M., Mallea, M.A., González, P., 2014. Assessment of the water self-purification capacity on a river affected by organic pollution: application of chemometrics in spatial and temporal variations. Environmental Science and Pollution Research 21, 10583-10593. http://doi.org/10.1007/s11356-014-3098-y.

Guerraiche, Z., 2017. Impact de la pollution urbaine sur les eaux de surface du Grand Constantinois. Université Mohamed Khider-Biskra.

Guidoum, A., 2017. Caractérisation Hydrologique Et Analyse De Transport Solide En Suspension Dans Trois Ensembles Hydrographiques Du Nord-Est Algérien Etude de cas dans la Seybouse, les hautes plaines constantinoises et Chott Melghir (Coupe Nord-sud). Université Mohamed Khider – Biskra, p. 369.

Haji Gholizadeh, M., Melesse, A.M., Reddi, L., 2016. Spaceborne and airborne sensors in water quality assessment. International Journal of Remote Sensing 37, 3143-3180. https://doi.org/10.1080/01431161.2016.1190477.

Hamiche, A.M., Stambouli, A.B., Flazi, S., 2015. A review on the water and energy sectors in Algeria: Current forecasts, scenario and sustainability issues. Renewable and Sustainable Energy Reviews 41, 261-276. https://doi.org/10.1016/j.rser.2014.08.024.

Hamil, S., Arab, S., Chaffai, A., Baha, M., Arab, A., 2018. Assessment of surface water quality using multivariate statistical analysis techniques: a case study from Ghrib dam, Algeria. Arabian Journal of Geosciences 11, 754.

Hamlat, A., Guidoum, A., Koulala, I., 2016. Status and trends of water quality in the Tafna catchment: a comparative study using water quality indices. Journal of Water Reuse and Desalination 7, 228-245. https://doi.org/10.2166/wrd.2016.155.

Hamlat, A., Tidjani, A.E.-B., Yebdri, D., Errih, M., Guidoum, A., 2013. Water quality analysis of reservoirs within Western Algeria catchment areas using water quality index CCME WQI. Journal of Water Supply: Research and Technology—AQUA 63, 311-324.

Hartigan, J.A., Wong, M.A., 1979. Algorithm AS 136: A k-means clustering algorithm. Journal of the Royal Statistical Society. Series C (Applied Statistics) 28, 100-108.

Hauer, F.R., Lamberti, G., 2011. Methods in stream ecology. Academic Press.

He, W., Chen, S., Liu, X., Chen, J., 2008. Water quality monitoring in a slightly-polluted inland water body through remote sensing — Case study of the Guanting Reservoir in Beijing, China. Frontiers of Environmental Science & Engineering in China 2, 163-171. https://doi.org/10.1007/s11783-008-0027-7.

Heddam, S., Lamda, H., Filali, S., 2016. Predicting Effluent Biochemical Oxygen Demand in a Wastewater Treatment Plant Using Generalized Regression Neural Network

Based Approach: A Comparative Study. Environmental Processes 3, 153-165. http://doi.org/10.1007/s40710-016-0129-3.

Helena, B., Pardo, R., Vega, M., Barrado, E., Fernandez, J.M., Fernandez, L., 2000. Temporal evolution of groundwater composition in an alluvial aquifer (Pisuerga River, Spain) by principal component analysis. Water Research 34, 807-816. https://doi.org/10.1016/S0043-1354(99)00225-0.

Horton, R.K., 1965. An index number system for rating water quality. Journal of Water Pollution Control Federation 37, 300-306.

Houria, B., Kalla, M., Tebbi, F.Z., 2020. Hydrochemical characterisation of groundwater quality: Merdja plain, Tebessa town, Algeria. Civil Eng J 6, 318-325.

Icaga, Y., 2007. Fuzzy evaluation of water quality classification. Ecological Indicators 7, 710-718. https://doi.org/10.1016/j.ecolind.2006.08.002.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An introduction to statistical learning. Springer.

Karakuş, C.B., 2019. Evaluation of water quality of Kızılırmak River (Sivas/Turkey) using geo-statistical and multivariable statistical approaches. Environment, Development and Sustainability, 1-35.

Kateb, Z., Bouchelkia, H., Benmansour, A., Belarbi, F., 2020. Sediment transport modeling by the SWAT model using two scenarios in the watershed of Beni Haroun dam in Algeria. Arabian Journal of Geosciences 13, 653. http://doi.org/10.1007/s12517-020-05623-0.

Kaufman, L., Rousseeuw, P,J, 1990. Finding groups in data: An introduction to cluster analysis. Hoboken NJ John Wiley & Sons Inc 725.

Kavurmaci, M., 2016. Evaluation of groundwater quality using a GIS-MCDA-based model: a case study in Aksaray, Turkey. Environmental Earth Sciences 75, 1258. http://doi.org/10.1007/s12665-016-6074-7.

Kavurmaci, M., Üstün, A.K., 2016. Assessment of groundwater quality using DEA and AHP: a case study in the Sereflikochisar region in Turkey. Environmental monitoring and assessment 188, 258. https://doi.org/10.1007/s10661-016-5259-6.

Kendall, M., 1975. Rank Correlation Methods. Charles Griffin 202, 15.

Kenneth, B.-A., William, G.A., 2012. Determination of the pollution loads of Brewery X and the impacts of the pollutant on the Sisai River. Journal of Public Health and Epidemiology 4, 316-319.

Khan, F., Husain, T., Lumb, A., 2003. Water Quality Evaluation and Trend Analysis in Selected Watersheds of the Atlantic Region of Canada. Environmental monitoring and assessment 88, 221-248. https://doi.org/10.1023/a:1025573108513.

Khedidja, A., Boudoukha, A., 2019. Quality assessment of shallow groundwater for irrigation purposes in Tadjenanet – Chelghoum Laid area (Eastern Algeria). International Journal of River Basin Management, 1-8. https://doi.org/10.1080/15715124.2019.1628031.

Khelif, S., Boudoukha, A., 2018. Multivariate statistical characterization of groundwater quality in Fesdis, East of Algeria. Journal of Water and Land Development 37, 65-74.

Kherief Nacereddine, S., Djeddi, H., Benayache, N.Y., Afri-Mehennaoui, F.Z., 2018. Nutrient and Phytoplankton Dynamics in the Beni Haroun Dam in Eastern Algeria. European Scientific Journal, ESJ 14, 111. http:/doi.org/10.19044/esj.2018.v14n12p111 (in French).

Landwehr, J.M., Deininger, R.A., McClelland, N.I., Brown, R.M., 1974. An objective water quality index. Journal of the Water Pollution Control Federation 46, 1804-1807.

Lenntech, 2020. Chemical properties of manganese - Health effects of manganese - Environmental effects of manganese online https://www.lenntech.com/periodic/elements/mn.htm. Accessed 14/05/2020.

Lermontov, A., Yokoyama, L., Lermontov, M., Machado, M.A.S., 2009. River quality analysis using fuzzy water quality index: Ribeira do Iguape river watershed, Brazil. Ecological Indicators 9, 1188-1197. https://doi.org/10.1016/j.ecolind.2009.02.006.

Li, P.Y., Qian, H., WU, J.H., 2010. Groundwater quality assessment based on improved water quality index in Pengyang County, Ningxia, Northwest China. E-Journal of Chemistry 7. https://doi.org/10.1155/2010/451304.

Liu, C.-W., Lin, K.-H., Kuo, Y.-M., 2003. Application of factor analysis in the assessment of groundwater quality in a blackfoot disease area in Taiwan. Science of The Total Environment 313, 77-89. https://doi.org/10.1016/S0048-9697(02)00683-6.

Lu, J., Ruan, D., 2007. Multi-objective group decision making: methods, software and applications with fuzzy set techniques. Imperial College Press.

Lu, R.-S., Lo, S.-L., 2002. Diagnosing reservoir water quality using self-organizing maps and fuzzy theory. Water Research 36, 2265-2274. https://doi.org/10.1016/S0043-1354(01)00449-3.

Lumb, A., Halliwell, D., Sharma, T., 2006. Application of CCME Water Quality Index to Monitor Water Quality: A Case Study of the Mackenzie River Basin, Canada. Environmental monitoring and assessment 113, 411-429. https://doi.org/10.1007/s10661-005-9092-6.

MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations, Proceedings of the fifth Berkeley symposium on mathematical statistics and probability. Oakland, CA, USA, pp. 281-297.

Mann, H.B., 1945. Nonparametric Tests Against Trend. Econometrica 13, 245-259. https://doi.org/10.2307/1907187.

Marouf, N., 2012. Study of water quality and sediment transport in the Beni-Haroun dam (MILA): its impact on the environment of the region. Mohamed Khider University, Biskra, Algeria, p. 242.

Marouf, N., Remini, B., 2016. Study of Beni Haroun dam pollution (Algeria). Desalination and Water Treatment 57, 2766-2774. https://doi.org/10.1080/19443994.2014.982192.

Mebarki, A., 2005. Hydrology of the Algerian Eastern basins: water resources, development and environment. University of Constantine, Algeria, p. 360.

Mebarki, A., Benabbas, C., Grecu, F., 2008. "Beni-Haroun" (Oued Kébir-Rhumel, Algeria) system: hydraulic developments and morpho-geological constraints (in French). Analele Universitatii Bucuresti: Geografie 57, 37-51.

Meddi, M., Toumi, S., 2014. Study of the interannual rainfall variability in northern Algeria. Revue LJEE.

Meddi, M., Toumi, S., 2015. Spatial variability and cartography of maximum annual daily rainfall under different return periods in Northern Algeria. Journal of Mountain Science 12, 1403-1421. 10.1007/s11629-014-3084-3.

Ministry of Water Resources (Ministère des Resources en Eaux) (MRE), 2016. http://www.mre.gov.dz/ (accessed 06.11.20).

Mladenović-Ranisavljević, I.I., Takić, L., Nikolić, Đ., 2018. Water Quality Assessment Based on Combined Multi-Criteria Decision-Making Method with Index Method. Water Resources Management 32, 2261-2276. https://doi.org/10.1007/s11269-018-1927-3.

Müller, B., Berg, M., Yao, Z.P., Zhang, X.F., Wang, D., Pfluger, A., 2008. How polluted is the Yangtze river? Water quality downstream from the Three Gorges Dam. Science of The Total Environment 402, 232-247. https://doi.org/10.1016/j.scitotenv.2008.04.049.

Mutikanga, H.E., Sharma, S.K., Vairavamoorthy, K., 2011. Multi-criteria Decision Analysis: A Strategic Planning Tool for Water Loss Management. Water Resources Management 25, 3947. https://doi.org/10.1007/s11269-011-9896-9.

National Research Council, 1999. Identifying future drinking water contaminants. National Academies Press.

Ocampo-Duque, W., Ferré-Huguet, N., Domingo, J.L., Schuhmacher, M., 2006. Assessing water quality in rivers with fuzzy inference systems: A case study. Environment International 32, 733-742. https://doi.org/10.1016/j.envint.2006.03.009.

Official Journal of the Algerian Republic (OJAR), 2011. The guidelines for Algerian drinking water quality. Off. J. Algerian Rep. 34, 17 Rajab 1432, 19 June 2011.

Oral, M., Oukil, A., Malouin, J.-L., Kettani, O., 2014. The appreciative democratic voice of DEA: A case of faculty academic performance evaluation. Socio-Economic Planning Sciences 48, 20-28. https://doi.org/10.1016/j.seps.2013.08.003.

Ott, W.R., 1978. Environmental indices: theory and practice. Ann Arbor Science Publishers Inc, Ann Arbor, MI.

Oukil, A., Govindaluri, S.M., 2017. A systematic approach for ranking football players within an integrated DEA-OWA framework. Managerial and Decision Economics 38, 1125-1136. 10.1002/mde.2851.

Oukil, A., Govindaluri, S.M., 2020. A hybrid multi-attribute decision-making procedure for ranking project proposals: A historical data perspective. Managerial and Decision Economics 41, 461-472.

Patroncini, D., 2013. Water quality investigations of the River Lea (NE London).

Peng, L., 2004. A universal index formula suitable to multiparameter water quality evaluation. Numerical Methods for Partial Differential Equations 20, 368-373. https://doi.org/10.1002/num.10090.

Prati, L., Pavanello, R., Pesarin, F., 1971. Assessment of surface water quality by a single index of pollution. Water Research 5, 741-751. https://doi.org/10.1016/0043-1354(71)90097-2.

Rail, C.D., 1989. Groundwater contamination: Sources, control, and preventive measures.

Ravikumar, P., Somashekar, R., Prakash, K., 2015. A comparative study on usage of Durov and Piper diagrams to interpret hydrochemical processes in groundwater from SRLIS river basin, Karnataka, India. Elixir International Journal 80, 31073-31077.

Remini, B., 2010. La problématique de l'eau en Algérie du nord. LARHYSS Journal P-ISSN 1112-3680/E-ISSN 2521-9782.

Remini, B., Hallouche, W., 2007. Studying sediment. Revue International Water Power et Dam construction. Octobre, 42-45.

Remini, B., Toumi, A., 2017. the Beni Haroun reservoir (algeria) is it threatened by siltation? LARHYSS Journal P-ISSN 1112-3680/E-ISSN 2521-9782, 249-263.

Rezak, S., Laborde, J.-P., Errih, M., 2012. Validation d'un modèle numérique de terrain adapté à la modélisation hydrologique régionale sur l'Algérie du Nord. Hydrological Sciences Journal 57, 928-941. https://doi.org/10.1080/02626667.2012.685742.

Rodier, J., Legube, B., Merlet, N., 2009. COLL. Water analysis (In French), 9th edition. Ed. Dunod Paris.

RStudio Team, 2019. RStudio: Integrated Development for R. RStudio, Inc., Boston.

Saaty, T.L., 1988. What is the analytic hierarchy process?, Mathematical models for decision support. Springer, pp. 109-121.

Samiotis, G., Trikoilidou, E., Tsikritzis, L., Amanatidou, E., 2018. Comparative water quality assessment between a young and a stabilized hydroelectric reservoir in Aliakmon River, Greece. Environmental monitoring and assessment 190, 234. https://doi.org/10.1007/s10661-018-6602-x.

Sargaonkar, A., Deshpande, V., 2003. Development of an Overall Index of Pollution for Surface Water Based on a General Classification Scheme in Indian Context.

Environmental monitoring and assessment 89, 43-67. https://doi.org/10.1023/a:1025886025137.

Scholz, M., 2016. Water Quality Standards. M. Scholz, Wetlands for Water Pollution Control (Second Edition)(págs. 1-7). Elsevier.

Semar, A., Saibi, H., Medjerab, A., 2013. Contribution of multivariate statistical techniques in the hydrochemical evaluation of groundwater from the Ouargla phreatic aquifer in Algeria. Arabian Journal of Geosciences 6, 3427-3436.

Şen, Z., 2017. Statistical Trend Tests, Innovative Trend Methodologies in Science and Engineering. Springer International Publishing, Cham, pp. 67-132.

Shi, W., Zeng, W., 2014. Application of k-means clustering to environmental risk zoning of the chemical industrial area. Frontiers of Environmental Science & Engineering 8, 117-127. https://doi.org/10.1007/s11783-013-0581-5.

Shrestha, S., Kazama, F., 2007. Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. Environmental Modelling & Software 22, 464-475. https://doi.org/10.1016/j.envsoft.2006.02.001.

Shrestha, S., Kazama, F., Nakamura, T., 2008. Use of principal component analysis, factor analysis and discriminant analysis to evaluate spatial and temporal variations in water quality of the Mekong River. Journal of Hydroinformatics 10, 43-56. https://doi.org/10.2166/hydro.2008.008.

Singh, K.P., Malik, A., Mohan, D., Sinha, S., 2004. Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of Gomti River (India)—a case study. Water Research 38, 3980-3992. https://doi.org/10.1016/j.watres.2004.06.011.

Smith, D.G., 1990. A better water quality indexing system for rivers and streams. Water Research 24, 1237-1244. https://doi.org/10.1016/0043-1354(90)90047-A.

Soltani, A.A., Oukil, A., Boutaghane, H., Bermad, A., Boulassel, M.-R., 2021. A new methodology for assessing water quality, based on data envelopment analysis: Application to Algerian dams. Ecological Indicators 121, 106952. https://doi.org/10.1016/j.ecolind.2020.106952.

Stallard, R., Edmond, J., 1983. Geochemistry of the Amazon: 2. The influence of geology and weathering environment on the dissolved load. Journal of Geophysical Research: Oceans 88, 9671-9688.

Sturges, H.A., 1926. The choice of a class interval. Journal of the american statistical association 21, 65-66.

Sutadian, A.D., Muttil, N., Yilmaz, A.G., Perera, B.J.C., 2017. Using the Analytic Hierarchy Process to identify parameter weights for developing a water quality index. Ecological Indicators 75, 220-233. https://doi.org/10.1016/j.ecolind.2016.12.043.

Taïbi, S., 2016. Influence de la circulation atmosphérique générale sur les précipitations du Nord de l'Algérie. Ecole Nationale Superieure d'Hydrauique (ENSH), Blida, Algeria, p. 196.

Tibshirani, R., Walther, G., Hastie, T., 2001. Estimating the number of clusters in a data set via the gap statistic. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 63, 411-423.

Touazi, M., Pierre Laborde, J., Bhiry, N., 2004. Modelling rainfall-discharge at a mean inter-yearly scale in northern Algeria. Journal of Hydrology 296, 179-191. https://doi.org/10.1016/j.jhydrol.2004.03.030.

Tramblay, Y., Jarlan, L., Hanich, L., Somot, S., 2018. Future Scenarios of Surface Water Resources Availability in North African Dams. Water Resources Management 32, 1291-1306. 10.1007/s11269-017-1870-8.

Tripathi, M., Singal, S.K., 2019. Use of Principal Component Analysis for parameter selection for development of a novel Water Quality Index: A case study of river Ganga India. Ecological Indicators 96, 430-436. https://doi.org/10.1016/j.ecolind.2018.09.025.

Tukey, J., W, 1977. Exploratory data analysis. Reading: Addison-Wesley.

Ukah, B., Ameh, P., Egbueri, J., Unigwe, C., Ubido, O., 2020. Impact of effluent-derived heavy metals on the groundwater quality in Ajao industrial area, Nigeria: an assessment using entropy water quality index (EWQI). International Journal of Energy and Water Resources, 1-14.

United Nations Development Programme (UNDP), 2009. Problems of the water sector and climate-related impacts in Algeria, 19 p.

Varol, M., Gökot, B., Bekleyen, A., Şen, B., 2012. Spatial and temporal variations in surface water quality of the dam reservoirs in the Tigris River basin, Turkey. CATENA 92, 11-21. https://doi.org/10.1016/j.catena.2011.11.013.

Varol, M., Şen, B., 2008. Assessment of surface water quality using multivariate statistical techniques: a case study of Behrimaz Stream, Turkey. Environmental monitoring and assessment 159, 543. https://doi.org/10.1007/s10661-008-0650-6.

Venkatramanan, S., Chung, S.Y., Kim, T.H., Kim, B.-W., Selvam, S., 2016. Geostatistical techniques to evaluate groundwater contamination and its sources in Miryang City, Korea. Environmental Earth Sciences 75, 994. https://doi.org/10.1007/s12665-016-5813-0.

Walski, T.M., Parker, F.L., 1974. Consumers water quality index. Journal of the Environmental Engineering Division 100, 593-611.

Wang, A., 2016. The Interaction of Iron with Proteins and Sugars in Biological Fluids and Beverages. Virginia Tech.

Wang, X., Cai, Q., Ye, L., Qu, X., 2012. Evaluation of spatial and temporal variation in stream water quality by multivariate statistical techniques: A case study of the

Xiangxi River basin, China. Quaternary International 282, 137-144. https://doi.org/10.1016/j.quaint.2012.05.015.

Wang, X., Ma, T., 2001. Application of remote sensing techniques in monitoring and assessing the water quality of Taihu Lake. Bulletin of environmental contamination and toxicology 67, 863-870.

Weatherill, G., Burton, P.W., 2009. Delineation of shallow seismic source zones using K-means cluster analysis, with application to the Aegean region. Geophysical Journal International 176, 565-588. https://doi.org/10.1111/j.1365-246X.2008.03997.x.

Wei, G., Yang, Z., Cui, B., Li, B., Chen, H., Bai, J., Dong, S., 2009. Impact of dam construction on water quality and water self-purification capacity of the Lancang River, China. Water Resources Management 23, 1763-1780.

World Health Organization (WHO), 2008. Guidelines for drinking water quality. WHO, Geneva.

World Health Organization (WHO), 2017. Guidelines for drinking-water quality: first addendum to the fourth edition.

Xiang, Z., Chen, X., Lian, Y., 2016. Quantifying the Vulnerability of Surface Water Environment in Humid Areas Base on DEA Method. Water Resources Management 30, 5101-5112. https://doi.org/10.1007/s11269-016-1471-y.

Yang, K., Trewn, J., 2004. Multivariate statistical methods in quality management. McGraw Hill Professional.

Yousefi, H., Zahedi, S., Niksokhan, M.H., 2018. Modifying the analysis made by water quality index using multi-criteria decision making methods. Journal of African Earth Sciences 138, 309-318. https://doi.org/10.1016/j.jafrearsci.2017.11.019.

Zahedi, S., 2017. Modification of expected conflicts between Drinking Water Quality Index and Irrigation Water Quality Index in water quality ranking of shared extraction wells using Multi Criteria Decision Making techniques. Ecological Indicators 83, 368-379. https://doi.org/10.1016/j.ecolind.2017.08.017.

Zahedi, S., Azarnivand, A., Chitsaz, N., 2017. Groundwater quality classification derivation using Multi-Criteria-Decision-Making techniques. Ecological Indicators 78, 243-252. https://doi.org/10.1016/j.ecolind.2017.03.015.

Zarei, H., Pourreza Bilondi, M., 2013. Factor analysis of chemical composition in the Karoon River basin, southwest of Iran. Applied Water Science 3, 753-761. https://doi.org/10.1007/s13201-013-0123-0.

Ziani, D., Boudoukha, A., Boumazbeur, A., Benaabidate, L., Fehdi, C., 2016. Investigation of groundwater hydrochemical characteristics using the multivariate statistical analysis in Ain Djacer area, Eastern Algeria. Desalination and Water Treatment 57, 26993-27002. https://doi.org/10.1080/19443994.2016.1180474.

Zou, H., Zou, Z., Wang, X., 2015. An enhanced K-means algorithm for water quality analysis of the Haihe River in China. International journal of environmental research and public health 12, 14400-14413.