Global NEST Journal, Vol 27, No 5, 07034

Assessment of water quality in two dams in semi-arid region dams of northeastern Algeria: using pollution indices

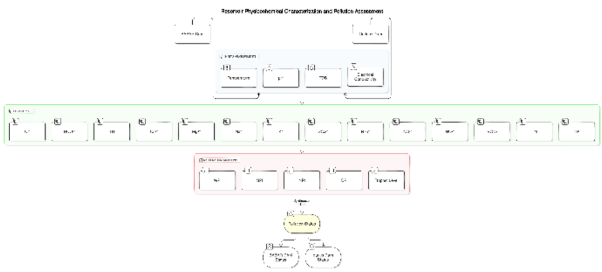
Zohra Sahraoui[1], Hichem Khammar[1], Saci Nadjai[2], Amin Chaffai[3], Nadhir Bouchema[1] and Ahlem Bourmada[1]

[1]Laboratory of Functional Ecology and Environment, Department of Life Sciences and Nature, Faculty of Exact Sciences and Life Sciences and Nature, University of "Larbi Ben M'hidi" Oum El Bouaghi, Oum elBouaghi 04000, Algeria

[2]Laboratory for fire safety engineering of buildings and protection of their urban and periurban environment, University Hassiba Benbouali of Chlef, BP 151, Chlef 02000, Algeria

[3] Laboratory of Dynamics and Biodiversity, Faculty of Biological Sciences, University of Science and Technology–Houari Boumediene, Algeria
Received: 16/11/2024, Accepted: 20/03/2025, Available online: 14/04/2025
*to whom all correspondence should be addressed: e-mail: hichem.khammar@univ-oeb.dz
https://doi.org/10.30955/gnj.07034

Graphical abstract



Abstract

This study investigates surface water pollution in two dams in northeastern Algeria: Ourkiss Dam in Oum El Bouaghi Province and Babar Dam in Khenchela Province, over a year (March 2023 to February 2024). The research assesses pollution levels, organic contamination, and nutrient status using several indices. The Water Pollution Index (WPI) indicated high pollution at 80% of Ourkiss Dam sites in spring, winter, and autumn, while 25% of Babar Dam sites were highly polluted in spring. Both dams showed moderate pollution levels in the remaining seasons. The Synthetic Pollution Index (SPI) classified all sites in both dams as moderately polluted year-round. The Nutrient Pollution Index (NPI) revealed no pollution in 25% of Ourkiss Dam sites and 75% of Babar Dam, while 70% and 25% of sites, respectively, experienced moderate pollution, with 5% of Ourkiss Dam severely polluted. The Organic Pollution Index (OPI) showed that 80% of Ourkiss Dam and 75% of Babar Dam sites were highly polluted. The Total Nitrogen to Total Phosphorus (TN) ratio classified 70% of stations at Ourkiss Dam as hypertrophic, 25% as mesotrophic, and 5% as eutrophic. Babar Dam had 60% hypertrophic, 15% mesotrophic, and 25% eutrophic stations. These results highlight significant pollution issues, particularly in Ourkiss Dam, and provide critical insights into the water quality and pollution management needs of both dams

Keywords : Algeria, dams, nutrients, pollution, semi-arid

1. Introduction

Water is essential for sustaining life and supporting social and economic activities. It is available in different forms, including surface water from rivers, lakes, and dams, as well as groundwater, sources are critical for drinking and irrigation (Ahmed, 2024). However, surface water pollution has emerged as a major environmental issue, driven by a range of biological and chemical contaminants (Al-Janabi *et al.*, 2019). Aquatic ecosystems face significant pressures from hydro-morphological changes, water abstraction, diffuse pollution sources particularly from agriculture and atmospheric deposition and point sources of pollution from industry and energy production (Dedić *et al.*, 2020); Rapid industrialization and urbanization also have led to a decline in air quality, which directly influences surface water. The high levels of CO_2 emissions from these processes dissolve into the water, resulting in increased mineralization, thereby altering the water's chemical composition (Periasamy *et al.*, 2024).

Increasing water scarcity and deteriorating water quality, especially in semi-arid regions, where water scarcity is intensified by reduced rainfall and uneven precipitation distribution, often falling below 300 mm per year, and the demand for water continues to rise with the increasing human population (Bouchema *et al.*, 2024). exacerbated by climate change, urbanization, and human activities, pose growing challenges (Jamali *et al.*, 2022). Surface water quality can also be compromised not only by human activities but also by natural events, such as floods. These events can alter water quality by carrying various pollutants into reservoirs or by affecting the concentration of water elements through dilution (Babu *et al.*, 2024). The scarcity of clean drinking water presents a significant threat to human health, which is further aggravated by the discharge of toxic industrial waste, untreated sewage, and hazardous materials into water bodies. Furthermore, insufficient knowledge, outdated treatment methods, and inadequate water quality monitoring systems further contribute to the decline in water quality (Kaler *et al*., 2019).

Assessing water quality is crucial for evaluating the health of watersheds and for informing management decisions to control both current and future pollution (Garizi, 2011). Various methods are used to assess water quality, including fuzzy comprehensive assessment (Liu *et al*., 2016), multivariate statistical methods (Alves *et al*., 2018), the artificial methods (Alves *et al*., 2018), artificial neural network method (Ahamed *et al*., 2019) and the comprehensive pollution index method (Tang *et al*., 2011). Water quality assessment involves monitoring both spatial and temporal parameters variations. (Zeinalzadeh, 2017; Ustaoˇglu, 2019), with the parameter showing the poorest quality often being used in multimetric assessment systems to determine the overall water quality class (Simonović *et al*., 2007).

The Water Pollution Index (WPI) is a widely used arithmetic method for integrating various physical, chemical, and biological parameters to evaluate the chemical and ecological status of water bodies (Filatov *et al*., 2005). The development and use of water quality indices have been discussed extensively in the literature (Rosenberg & Resh, 1993; Chapman, 1995). Various indices have been employed to assess water quality based on physical, chemical, and biological parameters. The Water Pollution Index (WPI) is an arithmetic method used to integrate these parameters in order to evaluate the chemical and ecological status of inland waters (Filatov *et al*., 2005).

The WPI, which relies on physical and chemical parameters, is applicable to rivers and other aquatic systems. Over-enrichment can result in harmful algal blooms, decreased dissolved oxygen levels in the water column, and reduced fish populations (Nixon *et al*., 1986; Taylor *et al*., 1999; Deegan *et al*., 2002). Increased nutrient inputs can also negatively impact seagrass survival and productivity by promoting the growth of phytoplankton, macroalgae, and other macroalgal species (Harlin and Thorne-Miller, 1981; Short, 1987; Short *et al*., 1995).

In recent decades, researchers have developed numerous methods to evaluate water quality in aquatic ecosystems, including the use of various water quality indices. These include the Water Quality Index (Kumar *et al*., 2014), the General Pollution Index (Sargaonkar and Deshpande, 2003), the Eutrophication Index (EI) (Liu *et al*., 2011), and the Organic Pollution Index (OPI) (Quan *et al*., 2005), among others. The OPI, introduced by Turki (2019), is designed to monitor temporal and seasonal changes in pollution due to organic contaminants. The term 'trophic status,' and its categories: oligotrophic, mesotrophic, eutrophic, and hypereutrophic; was originally introduced by Naumann in 1919 for classifying lakes (Busobozi, 2017); this concept is crucial for guiding research strategies and methods for lake restoration and protection. Monitoring water quality is vital for managing eutrophication and assessing lake productivity (Nojavan *et al*., 2019). Understanding a lake's trophic status provides insights into its productivity, water quality, biological health, and adherence to designated use criteria (Nojavan *et al*., 2019).

Lakes typically exhibit higher trophic status with increased concentrations of total nitrogen (TN) and total phosphorus (TP). Variations in nutrient levels significantly affect lake productivity and water clarity, impacting both biological and physical factors (Atique and An, 2020), even when the lake is supplied with treated water, it remains essential to maintain water parameter levels, particularly nutrient levels, as recycled water often contains high concentrations of specific nutrients like nitrogen and phosphorus(Selvanarayanan *et al*.,2024).The TN:TP ratio is often used to determine which nutrient is most limiting for algal growth in aquatic ecosystems (Maberly *et al*., 2020). Nitrogen and phosphorus generally influence phytoplankton growth according to Liebig's law of the minimum, where the scarcity of one nutrient limits growth, and changes in the availability of the other have minimal effect (Dolman & Wiedner, 2015).

The study area is located in a semi-arid region where water scarcity is a recurring challenge, influenced by geographic location, climate, and limited water resources (Kidou, 2021). The Increased demand for water, driven by agricultural and industrial expansion, urbanization, and population growth, has placed further strain on these resources. Local populations rely on surface water from reservoirs and private wells to meet their water needs (Brindha & Kavitha, 2015). Although there are indicators available to assess water quality, traditional methods for estimating water quality primarily rely on numerous manual tasks, including selecting river monitoring sites for examination and periodically collecting samples for lab analysis and evaluation (Ahmed *et al*., 2022). However, these conventional methods are prone to errors, and early detection is not possible. As a result, the need for more advanced water quality evaluation techniques has increased with the growth of artificial intelligence (AI) and computer technology (Venkatraman *et al*., 2024). Currently, machine learning (ML) and deep learning (DL) techniques, which are powered by artificial intelligence (AI), have shown significant potential and delivered promising results across a wide range of domains. These include financial forecasting, water preservation where they improve prediction accuracy, image recognition, which has seen advancements in object detection and classification, as well as natural language processing (NLP), where they enhance tasks such as language translation, sentiment analysis, and chatbots (Subramanian *et al*.,2024).

This study aims to analyze the spatial and temporal variations in water quality parameters at the Ourkiss and Babar Dams, located in the semi-arid northeastern region of Algeria. It focuses on evaluating pollution levels using indices such as the Water Pollution Index (WPI), Synthetic Pollution Index (SPI), Nutrient Pollution Index (NPI), and Organic Pollution Index (OPI). Additionally, the research assesses the trophic status of the dams throughout the year, based on the TN:TP ratio. Seasonal impacts on water quality and pollution levels will be examined, alongside an investigation into potential sources of contamination. The findings aim to provide actionable recommendations for sustainable water management while comparing water quality and pollution trends between the two dams.

2. Materials and methods

2.1. Study area

The study was conducted in the semi-arid region of northeastern Algeria, focusing on two dams located in neighboring provinces (wilayas): the Ourkiss Dam in Oum El Bouaghi and the Babar Dam in Khenchela.

The Ourkiss Dam lies within the Constantine Plateau, one of the largest wetland complexes in Algeria, and is situated in the Oum El Bouaghi province. Geographically, it is located at

35° 94' N latitude and 6° 25' E longitude, covering an area of 55 hectares (Dahdouh and Zarouki, 2020) (**Figure 1**). The dam is part of the Athmania water transfer system and contributes to the Beni Haroun regional water supply network (Monograph of Oum El Bouaghi, 2009). The region receives an annual rainfall between 200 and 400 mm, with temperatures ranging from 20°C to 40°C during April to September, and 8°C to 25°C between October and March (ANIREF and Monograph of Oum El Bouaghi, 2009). The surrounding area is composed primarily of sedimentary rocks from the Cretaceous and Neogene periods, along with Quaternary sediments. The terrain is dominated by dolomitic and calcareous formations, with clayey deposits in the Tapie area, particularly in the hills surrounding the dam (Monograph of Oum El Bouaghi, 2009).

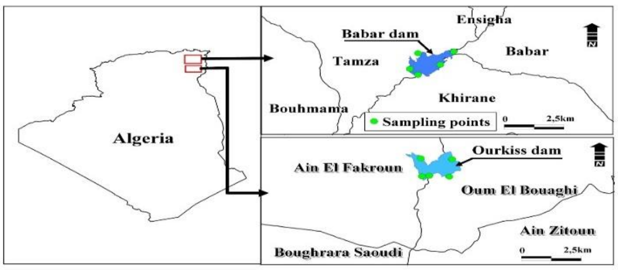


Figure 1. Geographical location of the two dams and the corresponding sampling points (ArcGIS 10.8)

The Babar Dam is located along the Wadi Arab in Khenchela Province. The dam is positioned at 35°10′10″ N latitude and 7°01′41″ E longitude (**Figure 1**), with a storage capacity of 54 million cubic meters, serving as a critical water reservoir for the region. The catchment area of the dam spans 567 km², and the Wadi Arab River, which feeds the dam, extends for 54 km. The region experiences a semi-arid climate, with an average annual rainfall of 310 mm and an average temperature of 15.2°C, according to data from 1988 to 2014 (Gaagai, 2009). The river flow is highly seasonal, peaking between October and April due to rainfall, and decreasing between May and September. The geology of the western basin area is dominated by sand, silt, and carbonate rocks, while the eastern region contains marl, anhydrite, gypsum, halite, and interbedded marly limestone (Gaagai, 2009).

The saline mineral formations in the region consist mainly of gypsum, followed by halite, glauberite, dolomite, mirabilite, quartz, epsomite, and pyrite (Vila, 1980). The climate around both dams is characterized by cold, wet winters and warm, dry summers, with annual rainfall ranging from 300 to 450 mm. In higher elevations, such as the surrounding mountainous areas, rainfall may exceed 600 mm, particularly during spring and late autumn (Tiri, 2010; ANBT, 2009).

2.2. Water sampling

From March 2023 to February 2024, water samples were collected monthly from five distinct stations at each dam, at a depth of 30 cm. This sampling method ensured the representativeness of the water across the dams. The collected data underwent statistical analysis, with mean, minimum, maximum, and standard deviation values calculated for each three-month period (season) **(Figure 1).**

2.3. Physico-chemical analysis

Water quality was assessed using a set of 18 different measurements. PH (Hydrogen Potential), TDS (Total Dissolved Solids), and EC (Electrical Conductivity) were measured on-site using a WTW 360 ODS Multi-Parameter device. Additionally, Chemical Oxygen Demand (COD) and Biological Oxygen Demand (BOD5) were recorded in milligrams per liter (mg/L). COD was determined using the Hach DR3900 instrument, while BOD5 was measured with the Hach BioTector B3500 instrument.

A comprehensive analysis of various chemical constituents was carried out at the Research Laboratory of Functional Ecology and Environment at Oum El Bouaghi University, using established protocols. Chloride (Cl^-) was quantified using the argentometric method, bicarbonate (HCO_3^- in mg/l) by arithmetic titration, and Total Hardness (TH) was determined by the $CaCO_3$ EDTA titrimetric method. Calcium (Ca^{2+}), sodium (Na^+), and potassium (K^+) concentrations were analyzed through flame photometry in the laboratory.

Nitrate (NO_3^-), nitrite (NO_2^-), ammonia (NH_4^+), orthophosphate (PO_4^{3-}), and sulfate (SO_4^{2-}) levels were determined using spectrophotometric methods. All physico-chemical analyses followed the methodologies recommended by Parsons *et al*. (1989), Aminot *et al*. (2007), and Rodier (2009).

Finally, the magnesium (Mg^{2+}) concentration was determined using the hardness equation after determining calcium content.

2.4. Calculation of the water pollution index (WPI)

A total of 11 water quality parameters were evaluated: pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Na^+, K^+, Mg^{2+}, Ca^{2+}, Bicarbonate (HCO_3^-), Cl^-, NO_3^-, and SO_4^{2-}. However, the Water Pollution Index (WPI) is designed to be flexible and can incorporate a larger number of variables, accommodating various parameters as needed. In the initial stage of the process, the pollution load (PLi) for parameter i was determined using the following formula:

$$PLi = 1 + \left(\frac{Ci - Si}{Si}\right) \quad (1)$$

where Ci represents the observed concentration of parameter i, and Si denotes the standard or maximum allowable limit for that parameter. The difference between Ci and Si is divided by Si to assess whether there has been an increase or decrease in the parameter value (PLi) relative to its standard allowable limit (Si). For pH, a value of 7 is considered neutral, while values below or above 7 are deemed detrimental. Based on these considerations, the following equations are proposed for different pH ranges. (Hossain and Patra, 2020)

$$PLi = \left(\frac{Ci - 7}{Si - 7}\right)$$

If PH < 7; Si=6.5 If PH > 7; Si=8.5

The pollution status of a water sample, or the Water Pollution Index (WPI), can be assessed by aggregating all pollution loads from the n variables (parameters) and then dividing by n. This is illustrated by the following formula. (Hossain and Patra, 2020).

$$WPI = \frac{1}{n}\sum_{i=1}^{n} PLi \quad (2)$$

In rare cases where the measured concentration of a parameter is 0, that value should be excluded from the total n for that sample.

The WPI values may be classified by a number of parameters into four distinct categories. **(Table 1)**

The WPI represents an integrated approach, consolidating all input parameters into a single index for water quality classification. As a result, even minor changes in the concentration of any individual parameter can significantly impact the WPI classification of water quality. (Hossain and Patra, 2020).

Table 1. Classification of water quality based on WPI scores

WPI value	Category
<0.5	Good
0.5 – 0.75	Excellent
0.75 – 1	Moderate pollution
>1	Highly polluted

Table 2. Water quality classification based on SPI classification standards (Gautam *et al*., 2015)

Range (SPI)	Type of surface water
SPI < 0.2	Suitable
0.2 ≤ SPI < 0.5	Slight pollution
0.5 ≤ SPI < 1.0	Moderate pollution
1.0 ≤ SPI < 3.0	High pollution
SPI ≥ 3.0	Unsuitable for drinking purposes

The WPI is adaptable and can be utilized with diverse datasets, including those with non-normally distributed or skewed variables. Moreover, relying on multiple indices for different purposes can be time-consuming in a single study. The WPI provides a comprehensive assessment of water quality across various parameters and can be customized for different objectives by applying the appropriate standard guideline values. (Hossain and Patra, 2020).

2.5. The synthetic pollution index (SPI)

The Synthetic Pollution Index (SPI) is a useful tool for assessing pollution levels in a specific area by combining multiple indicators into a single index. As outlined by Solongi *et al*. (2018), The SPI model involves three key steps: calculating the proportionality constant (Ki), applying the weighting coefficient (Wi), and deriving the synthetic pollution index (SPI).

Step1: The proportionality (Ki)

$$K = \frac{1}{\sum_{i=1}^{n} \frac{1}{Si}} \quad (3)$$

Step2: The weight coefficient (Wi)

$$Wi = \frac{Ki}{Si} \quad (4)$$

Step3: The synthetic pollution index (SPI)

$$SPI = \sum_{i=1}^{n} \frac{Ci}{Si} \times Wi \quad (3)$$

In this context:

n represents the number of water quality parameters under analysis.

Ci indicates the concentration (mg/l) of each physicochemical parameter in the sample, except pH and EC (µS/cm).

Si signifies the threshold value for each parameter, as outlined by the World Health Organization (WHO) guidelines and the SPI classification system.

Water quality can be categorized into one of five classes, as detailed in (**Table 2)**

2.6. Nutrient pollution index (NPI)

NPI is an important method for assessing drinking water quality in terms of nutrient contamination (Isiuku and Enyoh, 2020). The calculation formula for NPI is as follows:

$$NPI = \left(\frac{CN}{MAC_N}\right) + \left(\frac{CP}{MAC_P}\right) \quad (6)$$

In this formula, CN and CP denote the concentrations of nitrate (NO_3^-) and phosphate (PO_4^{3-}) in water samples, respectively, while MACN and MACP represent the maximum allowable concentrations of these nutrients as recommended by the World Health Organisation (WHO, 2011). The NPI scale is detailed in **Table 3**

Table 3. Water quality classification based on NPI standards

Range (NPI)	Water Quality Classes
NPI<1	No pollution
1≤NPI<3	Moderate polluted
3≤NPI≤6	Considerable polluted
NPI>6	Very high polluted

Table 4. Classification of organic pollution index (OPI) calculations and associated ranges

Class	BOD_5 (mg/ l)	NH_4^+ (mg/ l)	NO_2^- (µg /l)	PO_4^{3-} (µg /l)	Range (OPI)	Water Quality Classes
5	<2	<0.1	≤5	≤15	[1-2[	No organic pollution
4	2-5	0.1-0.9	6-10	16-75	[2-3[	Low organic pollution
3	5.1-10	1.0-2.4	11-50	76-250	[3-4[	Moderate organic pollution
2	10.1-15	2.5—6.0	51-150	251-900	[4-4.6[	High organic pollution
1	>15	>6	>150	>900	[4.6-5]	Very high organic pollution

Table 5. The TN: TP ratio (adapted and modified from Downing and McCauly, 1992; Yang *et al*., 2008)

Category	Description	TN:TP
Oligotrophic	A water body is characterised by a low supply of nutrients, a low production of organic matter, a low rate of decomposition, and a rapid cycling of nutrients.	> 100 No modification (Natural)
Mesotrophic	Waterbody with nutrient concentrations resulting in moderate productivity	51-100 Low modification
Eutrophic	Water is characterised by abundant nutrients and high productivity, often leading to oxygen depletion.	21-50 Intermediate modification
Hypertrophic	Waterbody is characterised by very low biodiversity, high productivity, excessive aquatic vegetation, and algal blooms.	<20 Extremely modified

2.7. Organic pollution index (OPI)

The OPI as defined by Leclercq and Maquet (1987), a saprobic index employed to identify organic pollution levels (Almeida, 2001). It uses four parameters: BOD_5, NH_4^+, NO_2^-, and PO_4^{3-} (**Table 4**). Each parameter is assigned a classification value from 1 to 5, based on its concentration in the water (Adour, 2001). The OPI is calculated as the average of these four values, resulting in a classification range from 1 to 5. A value of 1 indicates a high degree of organic pollution, whereas a value of 5 signifies no organic pollution (Yulianto *et al*., 2022) **(Table 4).**

2.8. Trophic status (the TN: TP ratio)

Monitoring nutrient concentrations is essential to protect the biological productivity of aquatic ecosystems. This approach ensures their sustainable use and the protection of the ecosystem services they provide (Malebo, 2023).

The ratio of total nitrogen to total phosphorus (TN: TP) is a widely used indicator for assessing limiting nutrients in surface waters, as described by Wetzel. (2001). The TN: TP ratios and their corresponding categories are based on the classifications by Downing and McCauly. (1992) and Yang *et al*. (2008), are presented in (**Table 5)**.

3. Results and discussion

3.1. Results

3.1.1. General hydrochemistry

The descriptive statistics of the physicochemical variables in this study include means, standard deviations, minimum and maximum values. These results are detailed for Ourkiss dam in **(Table 6)** and **(Figure 2)**, for Babar Dam in **(Table 7)** and **(Figure 3).**

The pH values is relatively alkaline, ranging from (7.6 ± 0.03) in the spring to (8.44 ± 0.07) in the summer at Ourkiss dam. While at Babar Dam, pH values range from (7.59 ± 0.04) in autumn to (8.03 ± 0.05) in summer.

The water is highly mineralised, as indicated by the Electrical Conductivity (EC) and Total Dissolved Solids (TDS) values. At Ourkiss Dam, EC and TDS range from (966 ± 99.12) µS/cm and (967 ± 99.73) mg/L in the summer to (1545.67 ± 103.84) µS/cm and (1543.67 ± 103.42) mg/L in the spring. Similarly, at Babar Dam, these values range from (871.33 ± 78.73) µS/cm and (871.67 ± 79.0) mg/L in summer to (1220.67 ± 43.57) µS/cm and (1220.67 ± 43.33) mg/L in spring respectively.

Most of the water samples exhibited concentrations of Mg^{2+}, Cl^-, and SO_4^{2-} exceeding the WHO guidelines, indicating elevated levels. At Ourkiss Dam, these values range from (42.92 ± 4.05) mg/L, (247.32 ± 20.95) mg/L, and (225.08 ± 11.39) mg/L in summer to (90.96 ± 7.69) mg/L, (337.25 ± 10.41) mg/L, and (335.47 ± 18.78) mg/L in spring. For Babar Dam, the corresponding values are (39.71 ± 5.58) mg/L, (142 ± 13.25) mg/L, and (279.69 ± 40.46) mg/L in summer, and (110.61 ± 12.40) mg/L, (295.83 ± 18.84) mg/L, and (471.43 ± 42.70) mg/L in spring, respectively.

Calcium (Ca^{2+}), Sodium (Na^{+}), and Potassium (K^{+}) levels were generally within the World Health Organization (WHO) limits, with a few exceptions. Sodium exceeded the recommended limits at both reservoirs during the spring, and potassium exceeded the limits at Ourkiss Dam in autumn and winter, despite the overall low values.

Concentrations of Nitrites (NO_2^-), Ammonium (NH_4^+), Orthophosphates (PO_4^{3-}), and Nitrates (NO_3^-) were generally negligible and did not exceed WHO standards in most samples. However, ammonium levels exceeded the WHO limit at site 4 of Ourkiss Dam during the summer (0.73 ± 0.16) mg/L) and at sites 3 (0.45 ± 0.09 mg/L) and 4 (0.60 ± 0.09 mg/L) in the autumn. Similarly, at Babar Dam, site 3 showed an exceedance in summer (0.46 ± 0.04 mg/L), and sites 1 (0.42 ± 0.03 mg/L) and 2 (0.45 ± 0.03 mg/L) in the autumn also surpassed the limit.

Biodegradability was assessed using biochemical oxygen demand (BOD_5). At Ourkiss Dam, BOD_5 values ranged from (76.92 ± 1.46) mg/L to (102.34 ± 1.39) mg/L, while at Babar Dam, they ranged from (82.45 ± 1.78) mg/L to (103.70 ± 1.39) mg/L. These values far exceeded the WHO standard range of (2–20) mg/L. The annual mean BOD_5 value was estimated at (89.58 ± 9.66) mg/L at Ourkiss Dam and (90.30 ± 4.86) mg/L at Babar Dam during the 2023–2024 period, both exceeding the WHO limit.

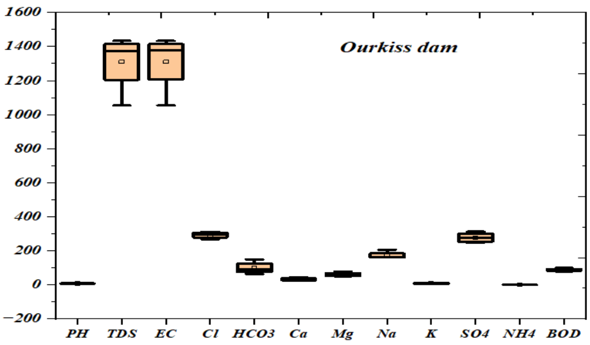


Figure 2. Box plots of the physicochemical parameters for Ourkiss dam 2023/2024

Previous studies on the Babar Dam (Gaagai, 2017) have shown that the parameters exceeding the limits set by WHO standards namely, EC, TDS, Cl^-, and SO_4^{2-} are consistent with those found in this study. The Ourkiss reservoir is part of the Beni Haroun regional water transfer system (Monograph Oum El Bouaghi, 2009), and previous research on the Beni Haroun Dam (Soltani, 2020) has shown a convergence in the values of some parameters with those observed at Ourkiss Dam, particularly for EC, TDS, Cl^-, and SO_4^{2-}.

Contaminants enter the water system from various sources, including industrial discharges, agricultural runoff, domestic wastewater, and other pollutants. Many of these sources, especially untreated ones, can have significant short- and long-term impacts on water quality (Singh *et al.*, 2007).

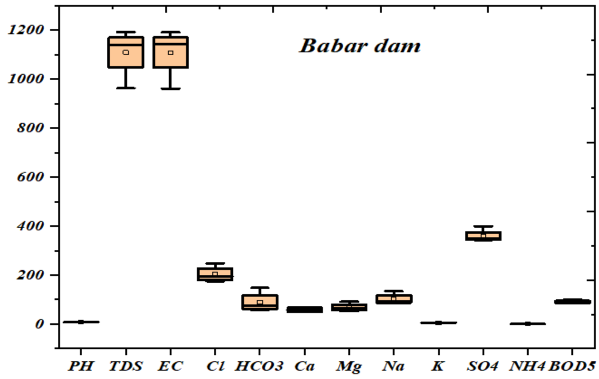


Figure 3. Box plots of the physicochemical parameters for Babar dam 2023/2024

3.1.2. Water pollution index (WPI)

The Water Pollution Index (WPI) integrates various water quality parameters to provide a streamlined evaluation of the physico-chemical and environmental status of surface waters (Hassan *et al.*, 2018). It offers a comprehensive assessment of both physical and chemical pollution in water.

According to the WPI classification **(Table 1)**, the water quality in Ourkiss and Babar reservoirs varied across the four seasons **(Figure 4).** The highest WPI value was recorded at site 1 in spring (1.19 ± 0.06), while the lowest value was observed at site 3 in summer (0.82 ± 0.06). with an estimated annual average of 1.04, classifying it under the high pollution category. Seasonal variations showed that 80% of the water at Ourkiss was highly polluted during spring, winter, and autumn, while 20% was moderately polluted during the summer.

At Babar Dam, the highest WPI value was recorded at site 5 in spring (1.17 ± 0.09), and the lowest at site 5 in summer (0.74 ± 0.09). The annual average WPI for Babar Dam was 0.94, placing it in the "moderate pollution" category. Water quality at Babar Dam was classified as "Highly Polluted" 25% of the time in spring and as "Moderately Polluted" 75% of the time during autumn, summer, and winter.

3.1.3. The synthetic pollution index (SPI)

The results of the Synthetic Pollution Index (SPI) are illustrated in (**Figure 5)**. Across all five sites and during all four seasons, 100% of the surface waters in both the Ourkiss and Babar reservoirs were classified as moderately polluted. At Ourkiss Dam, SPI values ranged from (0.72 ± 0.06) to (0.92 ± 0.06), while at Babar Dam, the SPI varied from (0.67 ± 0.04) to (0.86 ± 0.04).

Table 6. Seasonal Variation of Hydrochemical Parameters at Ourkiss Dam (March 2023 - February 2024) Compared to WHO (2011)

	WHO 2011	**6.5-8.5**	**500**	**500**	**250**	**200**	**300**	**75**	**45**	**200**	**12**	**250**	**0.4**	**0.2**	**50**	**5**	**20**	**50**	**5**
	Stations	**PH**	**TDS**	**EC**	**Cl^-**	**HCO_3^-**	**TH**	**Ca^{2+}**	**Mg^{2+}**	**Na^+**	**K^+**	**SO_4^{2-}**	**NH_4^+**	**NO_2^-**	**NO_3^-**	**PO_4^{3-}**	**BOD5**	**TN**	**TP**
Spring	SP_O1	7.60	1543.67	1545.67	307.67	162.67	122.37	55.94	66.44	200.66	8.08	335.47	0.17	0.063	0.380	0.09	84.08	75.35	0.67
	SP_O2	7.73	1514.67	1514.33	307.67	140.30	128.69	41.74	86.96	185.80	4.85	303.67	0.11	0.055	0.200	0.41	84.31	78.60	0.87
	SP_O3	7.67	1502.00	1498.00	307.67	113.87	132.69	41.74	90.96	186.19	3.49	274.17	0.17	0.038	0.260	0.09	100.69	57.20	0.73
	SP_O4	7.67	1429.33	1425.67	337.25	160.63	117.51	43.76	73.74	232.22	4.18	331.56	0.13	0.047	0.240	0.06	84.61	61.49	0.53
	SP_O5	7.67	1180.00	1180.33	295.83	166.73	114.26	35.65	78.61	224.95	3.25	317.13	0.14	0.040	0.640	0.07	78.51	70.02	0.80
	Mean	7.67	1433.93	1432.80	311.22	148.84	123.10	43.77	79.34	205.96	4.77	312.40	0.14	0.05	0.34	0.14	86.44	68.53	0.72
	Min	7.60	1180.00	1180.33	295.83	113.87	114.26	35.65	66.44	185.80	3.25	274.17	0.11	0.038	0.200	0.06	78.51	57.20	0.53
	Max	7.73	1543.67	1545.67	337.25	166.73	132.69	55.94	90.96	232.22	8.08	335.47	0.17	0.063	0.640	0.41	100.69	78.60	0.87
	SD	0.03	103.42	103.84	10.41	17.40	6.07	4.87	7.69	18.10	1.36	18.78	0.02	0.008	0.133	0.10	5.70	7.35	0.10
Summer	SU_O1	8.24	984.67	984.33	260.33	142.33	87.54	35.50	58.70	140.26	8.36	266.66	0.39	0.017	0.030	0.15	77.49	19.67	3.18
	SU_O2	8.44	967.00	966.00	248.50	61.00	64.72	15.80	48.92	152.98	5.93	225.08	0.17	0.024	0.020	0.10	76.92	11.55	4.03
	SU_O3	8.27	996.67	1000.33	247.32	80.00	68.72	25.79	42.92	148.79	7.04	241.93	0.38	0.022	0.020	0.14	79.08	16.04	3.24
	SU_O4	8.29	1303.00	1301.67	319.50	81.33	77.12	26.81	50.31	195.18	11.23	248.78	0.73	0.026	0.020	0.15	80.67	25.39	3.36
	SU_O5	8.14	1017.00	1017.00	260.00	73.20	76.71	23.77	52.94	165.88	7.92	256.27	0.15	0.019	0.030	0.31	80.97	22.76	25.39
	Mean	8.28	1053.67	1053.87	267.13	87.57	74.96	25.53	50.76	160.62	8.10	247.74	0.36	0.02	0.02	0.17	79.02	19.08	7.84
	Min	8.14	967.00	966.00	247.32	61.00	64.72	15.80	42.92	140.26	5.93	225.08	0.15	0.017	0.020	0.10	76.92	11.55	3.18
	Max	8.44	1303.00	1301.67	319.50	142.33	87.54	35.50	58.70	195.18	11.23	266.66	0.73	0.026	0.030	0.31	80.97	25.39	25.39
	SD	0.07	99.73	99.12	20.95	21.90	6.59	4.60	4.05	15.93	1.36	11.39	0.16	0.003	0.005	0.05	1.46	4.23	7.02
Autumn	AU_O1	7.71	1399.67	1400.67	295.83	97.60	85.78	34.92	50.85	162.32	11.87	270.71	0.37	0.020	0.260	0.13	84.80	24.72	2.21
	AU_O2	7.75	1404.33	1405.00	266.25	107.77	97.37	33.91	63.46	159.78	11.83	271.38	0.27	0.155	0.330	0.53	82.22	24.07	2.87
	AU_O3	7.88	1337.00	1338.67	284.00	113.87	87.38	31.88	55.50	150.98	10.91	243.47	0.45	0.176	0.290	0.37	87.72	26.76	2.75
	AU_O4	7.78	1420.00	1419.33	266.25	85.40	82.38	32.90	49.48	162.91	12.45	252.90	0.60	0.023	0.290	0.10	86.54	28.50	2.25
	AU_O5	7.68	1418.33	1418.33	337.25	93.53	84.79	34.50	49.86	166.43	12.72	262.14	0.39	0.029	0.120	0.49	90.18	32.91	2.23
	Mean	7.76	1395.87	1396.40	289.92	99.63	87.54	33.62	53.83	160.48	11.96	260.12	0.42	0.08	0.26	0.32	86.29	27.40	2.46
	Min	7.68	1337.00	1338.67	266.25	85.40	82.38	31.88	49.48	150.98	10.91	243.47	0.27	0.020	0.120	0.10	82.22	24.07	2.21
	Max	7.88	1420.00	1419.33	337.25	113.87	97.37	34.92	63.46	166.43	12.72	271.38	0.60	0.176	0.330	0.53	90.18	32.91	2.87
	SD	0.06	23.55	23.09	21.30	8.95	3.93	0.99	4.52	4.08	0.50	9.55	0.09	0.068	0.055	0.17	2.22	2.65	0.28
Winter	WI_O1	8.30	1365.67	1365.33	295.83	56.12	83.58	26.95	56.63	162.13	12.25	281.10	0.08	0.032	0.410	0.18	100.07	23.39	1.44
	WI_O2	7.76	1359.67	1361.33	301.75	77.27	84.38	26.95	57.43	161.35	12.40	303.92	0.08	0.030	1.420	0.18	100.98	27.63	1.40
	WI_O3	7.69	1343.67	1344.67	295.83	61.01	99.59	28.98	70.61	164.47	12.58	286.88	0.10	0.024	0.360	0.19	98.86	40.58	2.40
	WI_O4	8.37	1346.67	1350.33	266.25	60.60	73.58	25.94	47.64	165.26	12.58	291.88	0.11	0.025	0.350	0.23	102.34	30.73	1.99
	WI_O5	8.34	1365.33	1367.00	331.33	63.44	87.99	27.97	60.02	163.30	12.47	280.91	0.11	0.023	0.410	0.22	97.60	29.46	1.47
	Mean	8.09	1356.20	1357.73	298.20	63.69	85.82	27.36	58.47	163.30	12.46	288.94	0.10	0.03	0.59	0.20	99.97	30.36	1.74
	Min	7.69	1343.67	1344.67	266.25	56.12	73.58	25.94	47.64	161.35	12.25	280.91	0.08	0.023	0.350	0.18	97.60	23.39	1.40

	Max	8.37	1365.67	1367.00	331.33	77.27	99.59	28.98	70.61	165.26	12.58	303.92	0.11	0.032	1.420	0.23	102.34	40.58	2.40
	SD	0.29	8.83	8.19	14.67	5.43	6.37	0.89	5.48	1.25	0.10	7.17	0.01	0.003	0.332	0.02	1.39	4.24	0.36

All values (Means) are in mg/l except PH and EC (µ Siemens/cm), SD: standard deviation, SP: Spring; SU: Summer; AU: Autumn; WI: Winter; O: Ourkiss dam.

Table 7. Seasonal Variation of Hydrochemical Parameters at Babar Dam (March 2023 - February 2024) Compared to WHO (2011)

	WHO 2011	**6.5-8.5**	**500**	**500**	**250**	**200**	**300**	**75**	**45**	**200**	**12**	**250**	**0.4**	**0.2**	**50**	**5**	**20**	**50**	**5**
	Stations	**PH**	**TDS**	**EC**	**Cl^-**	**HCO_3^-**	**TH**	**Ca^{2+}**	**Mg^{2+}**	**Na^+**	**K^+**	**SO_4^{2-}**	**NH_4^+**	**NO_2^-**	**NO_3^-**	**PO_4^{3-}**	**BOD_5**	**TN**	**TP**
Spring	SP_B1	7.74	1202.67	1202.00	231.93	138.27	163.27	72.17	91.10	86.26	5.54	377.13	0.13	0.036	0.31	0.08	89.26	48.38	0.60
	SP_B2	7.70	1220.67	1220.67	248.50	130.13	152.10	78.25	73.85	126.15	4.87	398.11	0.22	0.020	0.11	0.09	89.88	56.35	0.43
	SP_B3	7.79	1084.00	1082.67	248.50	150.47	192.92	82.31	110.61	119.11	5.22	471.43	0.35	0.018	0.09	0.07	83.89	54.50	0.47
	SP_B4	7.75	1202.67	1201.00	218.92	154.53	181.70	78.25	103.45	116.96	5.94	434.72	0.27	0.032	0.14	0.09	85.97	49.69	0.51
	SP_B5	7.72	1251.67	1251.67	295.83	166.73	114.26	35.65	78.61	224.95	3.25	317.13	0.17	0.022	0.22	0.09	84.12	58.23	0.60
	Mean	7.74	1192.34	1191.60	248.74	148.03	160.85	69.33	91.52	134.69	4.96	399.70	0.23	0.03	0.17	0.08	86.62	53.43	0.52
	Min	7.70	1084.00	1082.67	218.92	130.13	114.26	35.65	73.85	86.26	3.25	317.13	0.13	0.018	0.09	0.07	83.89	48.38	0.43
	Max	7.79	1251.67	1251.67	295.83	166.73	192.92	82.31	110.61	224.95	5.94	471.43	0.35	0.036	0.31	0.09	89.88	58.23	0.60
	SD	0.02	43.33	43.57	18.84	11.06	22.14	13.47	12.40	36.11	0.72	42.70	0.07	0.007	0.07	0.01	2.36	3.52	0.06
Summer	SU_B1	7.83	871.67	871.33	189.33	69.13	103.24	48.11	55.13	99.47	3.53	355.11	0.33	0.042	0.08	0.16	88.66	20.64	1.29
	SU_B2	7.87	1043.67	1042.00	183.42	71.17	112.07	52.17	59.90	86.88	5.54	362.13	0.34	0.057	0.14	0.16	82.98	14.58	2.86
	SU_B3	7.87	1043.67	1042.00	183.42	71.17	112.07	52.17	59.90	86.88	5.54	362.13	0.46	0.050	0.14	0.21	84.99	14.99	3.47
	SU_B4	7.89	998.67	998.00	177.50	61.00	102.85	49.13	53.72	135.81	5.20	339.13	0.32	0.052	0.12	0.32	82.45	12.68	1.33
	SU_B5	8.03	856.33	855.33	142.00	54.90	90.86	51.15	39.71	85.98	4.23	323.22	0.38	0.042	0.10	0.13	85.59	10.72	2.93
	Mean	7.90	962.80	961.73	175.13	65.47	104.22	50.55	53.67	99.00	4.81	348.34	0.36	0.05	0.12	0.20	84.93	14.72	2.38
	Min	7.83	856.33	855.33	142.00	54.90	90.86	48.11	39.71	85.98	3.53	323.22	0.32	0.042	0.08	0.13	82.45	10.72	1.29
	Max	8.03	1043.67	1042.00	189.33	71.17	112.07	52.17	59.90	135.81	5.54	362.13	0.46	0.057	0.14	0.32	88.66	20.64	3.47
	SD	0.05	79.04	78.72	13.25	6.02	6.28	1.54	5.58	14.91	0.74	13.74	0.04	0.005	0.02	0.06	1.78	2.48	0.85
Autumn	AU_B1	7.59	1140.00	1138.33	230.75	48.80	110.53	62.31	48.21	83.75	5.82	279.69	0.42	0.040	0.31	0.09	90.59	23.26	1.53
	AU_B2	7.69	1115.00	1115.00	183.42	63.03	96.55	67.39	40.45	96.89	6.25	307.71	0.45	0.029	0.24	0.03	91.05	25.34	1.37
	AU_B3	7.69	1142.33	1142.33	224.83	113.87	131.74	65.36	66.39	82.73	6.65	343.00	0.40	0.028	0.26	0.07	86.88	27.42	1.31
	AU_B4	7.60	1145.00	1144.00	207.08	105.73	127.72	61.30	66.42	81.95	6.23	360.74	0.37	0.028	0.24	0.06	87.94	27.89	1.11
	AU_B5	7.66	1134.33	1134.00	177.50	93.53	137.74	64.34	73.39	83.12	6.35	428.09	0.37	0.028	0.43	0.04	90.71	26.86	1.34
	Mean	7.65	1135.33	1134.73	204.72	84.99	120.86	64.14	58.97	85.69	6.26	343.85	0.40	0.03	0.30	0.06	89.44	26.15	1.33
	Min	7.59	1115.00	1115.00	177.50	48.80	96.55	61.30	40.45	81.95	5.82	279.69	0.37	0.028	0.24	0.03	86.88	23.26	1.11
	Max	7.69	1145.00	1144.00	230.75	113.87	137.74	67.39	73.39	96.89	6.65	428.09	0.45	0.040	0.43	0.09	91.05	27.89	1.53
	SD	0.04	8.53	8.19	19.40	23.26	13.85	1.87	11.71	4.48	0.19	40.46	0.03	0.004	0.06	0.01	1.62	1.48	0.10
Winter	WI_B1	7.63	1155.33	1155.33	195.25	57.75	120.98	49.27	71.71	89.18	6.38	367.31	0.15	0.027	0.27	0.14	103.70	26.98	1.62
	WI_B2	7.67	1135.67	1133.67	165.67	69.14	116.32	49.27	67.05	88.40	7.25	370.80	0.17	0.026	0.27	0.19	100.18	22.98	1.50
	WI_B3	7.54	1136.00	1136.00	183.42	61.00	116.51	49.27	67.24	89.57	6.35	328.48	0.14	0.028	0.36	0.15	98.59	22.49	2.07

WI_B4	7.62	1159.67	1159.67	177.50	56.94	122.69	48.26	74.44	89.57	6.33	367.70	0.15	0.024	0.41	0.24	99.73	21.87	2.37
WI_B5	7.58	1151.67	1159.67	201.17	42.30	111.92	50.29	61.64	88.60	6.21	316.58	0.16	0.021	0.30	0.22	98.93	23.20	1.94
Mean	7.61	1147.67	1148.87	184.60	57.43	117.68	49.27	68.42	89.06	6.50	350.17	0.15	0.03	0.32	0.19	100.23	23.51	1.90
Min	7.54	1135.67	1133.67	165.67	42.30	111.92	48.26	61.64	88.40	6.21	316.58	0.14	0.021	0.27	0.14	98.59	21.87	1.50
Max	7.67	1159.67	1159.67	201.17	69.14	122.69	50.29	74.44	89.57	7.25	370.80	0.17	0.028	0.41	0.24	103.70	26.98	2.37
SD	0.04	9.47	11.23	10.89	6.24	3.32	0.41	3.73	0.45	0.30	22.12	0.01	0.002	0.05	0.03	1.39	1.39	0.27

All values (Means) are in mg/l except PH and EC (µ Siemens/cm), SD: standard deviation, SP: Spring; SU: Summer; AU: Autumn; WI: Winter; B: Babar dam.

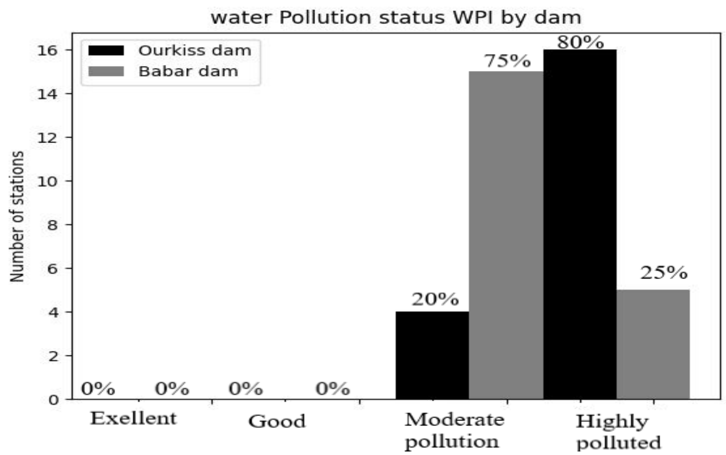


Figure 4. Water Pollution Index (WPI) for the Ourkiss and Babar Dams during the four seasons

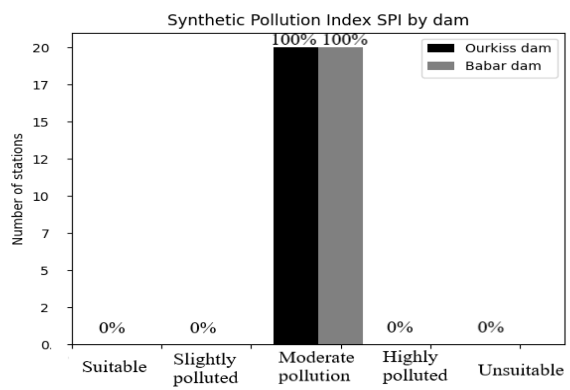


Figure 5. Synthetic Pollution Index (SPI) for the Ourkiss and Babar Dams during the four seasons

3.1.4. Nutrient pollution index (NPI)

The **Nutrient Pollution Index (NPI)** is a critical tool for assessing water quality, particularly in relation to nitrate contamination (El-Haji *et al*., 2024). Nitrates, originating primarily from agricultural runoff, industrial discharges, and municipal wastewater, are a significant contributor to water pollution, posing risks to both human health and aquatic ecosystems. (El-haji *et al*., 2024).

In this study, the annual average NPI for both dams were (1.4 ± 0.56). At Ourkiss Dam, NPI values ranged from a minimum of 0.76 to a maximum of 5.53, while Babar Dam values ranged between 0.52 and 1.25.

Further analysis revealed that 25% of the sites at Ourkiss Dam (AU_O1, WI_O1, WI_O2, SU_O3, and WI_O5) showed no pollution, 70% of the sites indicated moderate pollution, and one site (SU_O5) exhibited severe pollution (5%). In contrast, Babar Dam had 75% of its sites classified as no pollution., while 25% of the sites showed moderate pollution, particularly during the spring season. These findings underscore the prevalence of nitrate contamination in the study area **(Figure 6).**

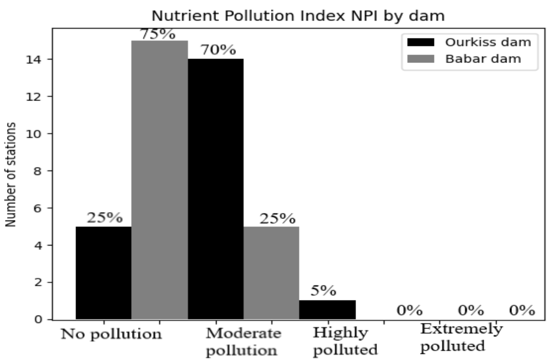


Figure 6. Nutrient Pollution Index (NPI) for the Ourkiss and Babar Dams during the four seasons

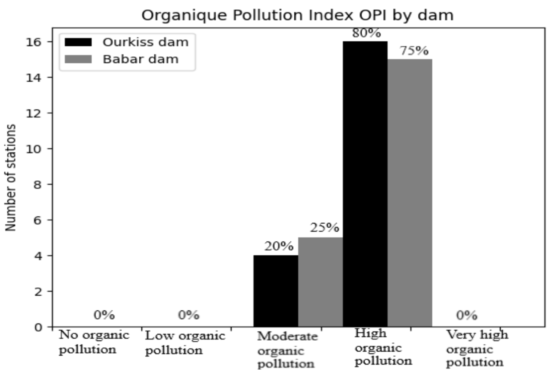


Figure 7. Organic Pollution Index (OPI) of the two dams (Ourkiss and Babar)

3.1.5. Organic pollution index (OPI)

The Organic Pollution Index (OPI) exhibited seasonal variations across the sites in both the Ourkiss and Babar Dams. During the study period, moderate organic pollution was observed at 20% of the sites in the Ourkiss Dam, including WI_O1, WI_O2, SP_O4, and SP_O5, with an average OPI value of (3±0.22). Similarly, 25% of the sites in the Babar Dam, including SP_B3, AU_B2, AU_B3, AU_B4, and AU_B5, also recorded moderate organic pollution, with the same OPI value of (3±0.22). In contrast, 80% of the remaining sites in the Ourkiss Dam and 75% in the Babar Dam were classified as highly polluted; the OPI values for these sites varied from (2.25 ± 0.22) to (2.75 ± 0.22) across both dams **(Figure 7)**.

3.1.6. Trophic status (TN: TP)

From March 2023 to February 2024, the TN: TP ratio at the Ourkiss Dam exhibited significant seasonal variation. The highest TN: TP values were recorded in spring, with an average of (83.98 ± 8.83), reflecting high total nitrogen concentrations and low total phosphorus levels, placing the dam in the mesotrophic range. Conversely, the lowest values were recorded in summer, with a mean of (5.15 ± 1.38), indicating a hypertrophic condition characterized by elevated total phosphorus and decreased total nitrogen levels. At the Babar Dam, the highest TN: TP values were also recorded in spring, with a mean of (65.47 ± 31.79), particularly at sites 1, 4, and 5, suggesting a mesotrophic condition due to high nitrogen and low phosphorus concentrations. The lowest values were observed during summer, with a mean of (7.73 ± 4.04), indicating a shift toward hypertrophic conditions with relatively higher phosphorus and lower nitrogen levels. Throughout the study year at the Ourkiss Dam, 14 samples (70%) were classified as hypertrophic, 5 samples (25%) as mesotrophic, and 1 sample (5%) as eutrophic. At the Babar Dam, 12 samples (60%) were hypertrophic, 3 samples (15%) were mesotrophic, and 5 samples (25%) were eutrophic (**Figure 8**).

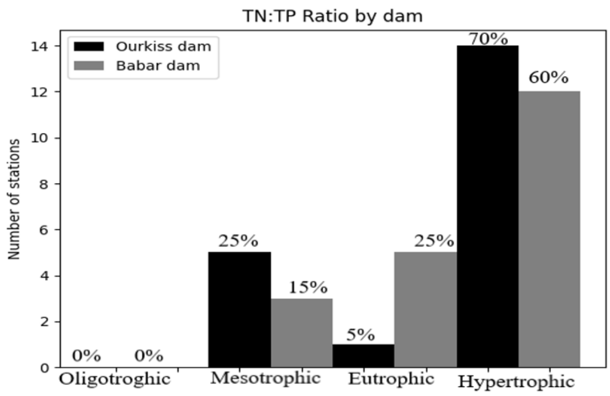


Figure 8. Trophic Status (TN: TP) results and classifications for both the Ourkiss and Babar Dams

4. Discussion

This study assesses water pollution in the Ourkiss and Babar dams, situated in the semi-arid region of northeastern Algeria, focusing on the physical and chemical parameters of surface water during the 2023-2024 period. The water pollution indicators were calculated based on 18 studied physicochemical parameters **(Tables 6 and 7)**. Several of these parameters exceeded the WHO (2011) limits for safe drinking water.

The highest recorded values of EC and TDS in both reservoirs suggest deteriorating water quality. This decline could be attributed to various anthropogenic activities, such as agricultural runoff, urbanization, or industrial pollution (Bouchareb, 2023), as well as natural causes like the solubility of evaporite minerals such as gypsum, anhydrite, and halite (Nas, 2010; Pacini, 2013). The mean annual TDS and EC values for Babar Dam were (1109.53 ± 72.30) mg/l and (1109.23 ± 72.77) µS/cm, respectively, while the Ourkiss Dam had higher values of (1309.92 ± 141.12) mg/l and (1310.2 ± 141.15) µS/cm.

Studies by Gui (2021) showed that internal erosion during heavy rainfall could increase the permeability of tailings, potentially affecting water conductivity in the dam. In the case of Babar Dam, slight elevations in conductivity could be linked to runoff from the surrounding watershed interacting with mountain rocks, a finding consistent with Khadka *et al*. (2020). Two key factors contributing to elevated parameters like total hardness (TH), EC, and TDS are soil erosion and the regional geology. These parameters act as reliable indicators of inorganic pollution (Turner & Rabalais, 2003).

In particular, the concentration of Chloride (Cl^-) in Ourkiss Dam exceeded the WHO's safe limit of 250 mg/l for drinking water, with an annual mean concentration of (292 ± 23.4) mg/l. Elevated chloride levels increase water corrosiveness, which can negatively affect human health, causing irritation of the eyes, nose, and stomach (Patil, 2012). Additionally, high chloride concentrations may indicate the influx of highly saline water into the reservoir (Supriyadi, 2017). For irrigation purposes, Chloride concentrations between 70 and 350 mg/l can cause moderate to serious issues for plant growth, especially when concentrations exceed 350 mg/l (Mass, 1990).

The two reservoirs exhibit high concentrations of SO_4^{2-}, primarily due to the presence of evaporite formations in the area. Additionally, wastewater discharge from urban sectors contributes to increased SO_4^{2-} levels (Kura, 2014). The extensive use of sulfate fertilizers in intensive agriculture further elevates SO_4^{2-} concentrations, especially following rainfall, as runoff transports excess sulfate into surface waters (Guergazi *et al*., 2006). In semi-arid regions, sporadic and variable rainfall, such as the events of late May and June 2023, exacerbates this issue.

Mg^{2+} concentrations in both dams are linked to the dissolution of gypsum and epsomite (Gaagai, 2017). Magnesium concentrations in both reservoirs exceed the WHO (2011) guidelines of 45 mg/L, with substantial variability over time (Gaagai, 2021). This variation can be attributed to land leaching and effluent discharges following torrential rainfall (Gaagai, 2021).

Nutrient levels were within acceptable ranges in both reservoirs, consistent with findings from other studies on dams located in semi-arid regions. However, BOD_5, a measure of the oxygen required by microorganisms to decompose organic matter over five days (Al-Saadi, 2006); The results for this parameter showed elevated BOD_5 levels throughout most of the year, likely due to higher temperatures that promote microbial activity and consequently increase oxygen consumption. Additionally, reduced water levels in the reservoirs concentrated pollutants, particularly during dry periods, further elevating BOD_5 values (Prathumratana *et al*., 2008). The highest BOD_5 values were recorded during the study period, exceeding WHO limits due to the lack of rainfall, which resulted in increased organic matter discharge into both reservoirs.

The WPI calculated values for the Babar and Ourkiss dams indicates that water quality ranged from moderately to highly polluted during the period March 2023 to February 2024. This pollution poses a major concern for the local population, who rely on the reservoirs for drinking water and various other activities. Several factors contribute to the decline in water quality, including the geological characteristics of the area, intensive agricultural practices, sewage discharge, and runoff following occasional rainfall (Chaminé *et al*., 2018). These factors have resulted in high concentrations of EC, TDS, Mg^{2+}, SO_4^{2-}, and Cl^-. The pollution patterns observed in these reservoirs are similar to those found in other semi-arid and desert regions. For instance, studies conducted in Iraq (Hassan *et al*., 2018) and Algeria (Maden *et al*., 2023) on the Shatt Al-Basrah Canal and Ouled Mellouk Dam, respectively, reported similar levels of pollution, ranging from moderate to high polluted', as observed in the Ourkiss and Babar dams.

As for the SPI, it indicates that the water in both dams is moderately polluted across all sites and seasons. This is due to high concentrations of parameters such as TDS, EC, Mg^{2+}, Cl^-, and SO_4^{2-}. The study further demonstrated that both the SPI and WPI are influenced by the same parameters, resulting in nearly identical outcomes, particularly at Babar Dam, where both indices classified the water as 'moderately polluted' (100% for SPI and 75% for WPI).

The Nutrient Pollution Index (NPI) ranged from no pollution to high pollution at Ourkiss Dam, whereas at Babar Dam, the NPI fluctuated from no pollution to moderate pollution. This variation is attributed to agricultural activities, particularly the application of nitrogen- and phosphorus-based fertilizers, which progressively increase the concentrations of these compounds in both the water and soil (Wetzel, 2001; Manahan, 2011). The primary sources of nitrogen and phosphorus compounds in groundwater and surface waters are anthropogenic activities, including fertilizer use, animal feed operations, municipal wastewater, sewage sludge, and septic tanks (Tokatli, 2014).

For both Ourkiss and Babar dams, the Organic Pollution Index (OPI) ranged from moderate to severe. This was likely due to domestic sewage inputs, particularly at Babar Dam, which is closer to population centers. Both dams are also impacted by agricultural residues, which contribute significantly to surface water pollution (Saleem & Hussain, 2013).

The TN:TP ratio, which measures total dissolved nitrogen relative to total dissolved phosphorus, showed important variations across the study period (Malibu, 2023). An increased TN:TP ratio indicates higher TN and lower TP, while a decreased ratio suggests a rise in TP and a reduction in TN, indicating nitrogen-limited conditions. This imbalance can exacerbate eutrophic conditions in both reservoirs (Malibu, 2023). The High phosphorus concentrations recorded during summer and autumn may be attributed to internal phosphorus recycling, which occurs through fish excretion and bioturbation of sediments by bottom-feeding fish (Hart & Harding, 2015). In contrast, low TP levels may result from phosphate sedimentation processes (Nikolai, 2014; Chung, 2009). The high nitrogen concentrations observed in both reservoirs during spring are likely due to wastewater inflows from nearby residential areas and agricultural runoff rich in nitrogen compounds.

5. Conclusion

This study highlights that the water quality of the Ourkiss and Babar reservoirs is significantly influenced by a complex interplay of physicochemical parameters, classification methods, and natural as well as anthropogenic factors. The results indicated that rainfall patterns, geological features, and agricultural activities in the surrounding areas were the primary factors influencing water quality in both reservoirs. Specifically, the main water quality indicators identified were TDS, which ranged from 967 to 1543.67 mg/L in Ourkiss and 856 to 1251.67 mg/L in Babar. EC values varied between 966 and 1545 µS/cm in Ourkiss and 855 to 1251 µS/cm in Babar. TN and TP concentrations exceeded the World Health Organization standards. Additionally, Mg^{2+} levels surpassed 90 mg/L in Ourkiss and exceeded 110 mg/L in Babar during certain seasons. Similarly, SO_4^{2-} concentrations also peaked in Babar, reaching a maximum of 471.43 mg/L.

The assessment methods used Including the Water Pollution Index (WPI), Synthetic Pollution Index (SPI), Nutrient Pollution Index (NPI), Organic Pollution Index (OPI), and the total nitrogen to total phosphorus (TN:TP) ratio, were effective for tracking water quality trends and pollution levels over time and across various geographical regions for drinking and irrigation applications. The findings for 2023/2024 revealed that Ourkiss Dam was moderately polluted at 20% of its sites and highly polluted at 80%, according to the WPI analysis. In contrast, Babar Dam exhibited moderate pollution at 75% of its sites and high pollution at 25%. Both dams were classified as moderately polluted across 100% of sites using the SPI. Nutrient pollution, as assessed by the NPI, revealed varying levels of impact: 25% of sites at Ourkiss Dam were not polluted, 70% were moderately polluted, and 5% were heavily polluted. At Babar Dam, 75% of sites showed no pollution, while 25% exhibited moderate nutrient pollution. The Organic Pollution Index (OPI) classified Ourkiss Dam as having moderate organic pollution at 20% of sites and high organic pollution at 80%, while Babar Dam had moderate pollution at 25% of sites and high pollution at 75%. The TN:TP ratio served as an important environmental indicator for nutrient status. Ourkiss Dam was classified as mesotrophic at 25% of its sites, eutrophic at 5%, and hyper-eutrophic at 80%. To improve water quality and ensure sustainable dam management, the study recommends close monitoring of fish farming practices and fertiliser application in both regions. Implementing these measures will contribute to safeguarding the reservoirs' ecological balance and enhance water quality for various uses. Dams are a critical component of national water infrastructure, fulfilling essential roles in providing water for drinking, irrigation, and industrial purposes. Given their importance, the continuous monitoring and assessment of dam water quality are crucial. Advanced methods, such as machine learning (ML) techniques, present innovative solutions for predicting dam water quality. Specifically, the application of Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs) enables accurate prediction of water quality trends by accounting for various influencing factors, particularly climatic conditions. Artificial intelligence (AI) significantly enhances these predictive models, enabling decision-makers with the tools to implement proactive measures to mitigate water quality deterioration and prevent potential system failures.

References

Adour G., (2001). Le nouveau système d'évaluation de la qualité de l'eau des rivières : le seq-eau François simonet. *Revue de l'Agence de l'Eau* N **81**

Agence Nationale d'Intermédiation et de Régulation Foncière (*ANIREF*)

Ahamad K.U., Raj, P., Barbhuiya N.H., Deep A., (2019). Surface Water Quality Modeling by Regression Analysis and Artificial Neural Network. In Advances in Waste Management; *Springer: Singapore*. 215–230, Available online: https://link.springer.com/chapter/10.1007/978-981-13-0215-2_15

Ahmed M., Mumtaz R. and Anwar Z. (2022). An enhanced water quality index for water quality monitoring using remote sensing and machine learning. *Applied Sciences*, ***12***(24), 12787.

Ahmed S. (2024). Assessment of Groundwater Quality in Union Councils Ratokot and Khairpur Juso. Pakistan, for Drinking Water Usage through Synthetic Pollution Index (SPI) and Water Quality Index (WQI): *A Case Study*.

Al-Janabi Z., Zaki S.R., AlHassany J.S., Al-Obaidy A.H.M., Awad E. and Maktoof A.A. (2019). Geochemical Evaluation of Heavy Metals (Cd, Cr, Fe, and Mn) in Sediment of Shatt Al-Basrah, Iraq. *Engineering and Technology Journal*, **37**(2C), 237–241.

Almeida S.F.P. (2001). Use of diatoms for freshwater quality evaluation in Portugal. *Limnetica,* **20**(2), 205–213.

Al-Saadi H.A. (2006). Fundamental of ecology. First printing, *Dar Al-Bazordi for printing and publishing, Amman-Jordan*: 411pp (In Arabic).

Alves D.D., Riegel R.P., De D.Q., Osório D.M.M., Da G.C., Do C.N. and Telöken F. (2018). Seasonal assessment and apportionment of surface water pollution using multivariate statistical methods: Sinos River, southern Brazil. *Environ. Monit. Assess*. **190**, 384.

Arun Mozhi Selvi Sundarapandi., Sundara Rajulu Navaneethakrishnan., Hemlathadhevi A., Surendran Rajendran., (2024). A Light weighted Dense and Tree structured simple recurrent unit (LDTSRU) for flood prediction using meteorological variables, *Global NEST Journal*, **26**(8), 06242. https://doi.org/10.30955/gnj.06242

Atique U. and An K-G. (2020). Landscape heterogeneity impacts water chemistry, nutrient regime, organic matter and chlorophyll dynamics in agricultural reservoirs. *Ecol Ind* **110**, 105813.

Babu T., Raveena Selvanarayanan., Tamilvizhi Thanarajan and Surendran Rajendran. (2024). Integrated early flood prediction using sentinel-2 imagery with VANET-MARL-based deep neural RNN, *Global NEST Journal*, **26**(10), 06554. https://doi.org/10.30955/gnj.06554

Bouchareb N., Khammar H., Bousbia S., Lefilef A., Boudeffa K., Akboudj A., Chardib M. and Bouguenna R. (2024), Anthropogenic Influence and Climate Change: Water and Nutrient Dynamics in the Kebir-Rhumel Basin, (Northeastern Algeria), *Global NEST Journal*, **26**(7),06014. https://doi.org/10.30955/gnj.06014

Bouchema N., Khammar H., Nadjai S., Tellil B. and Zeghdani Z., (2024). Assessment of surface water quality for drinking and irrigation purposes in two dams in the semi-arid region of Northeast Algeria. *Global NEST Journal*, **26**(8), 05912. https://doi.org/10.30955/gnj.005912.

Brindha K. and Kavitha R.J.E.E.S. (2015). Hydrochemical assessment of surface water and groundwater quality along Uyyakondan channel, south India. *Environmental Earth Sciences,* **73**, 5383–5393.

Busobozi E. (2017). Eutrophication in Ugandan crater lakes: a case study of six crater lakes located in Kabarole district Western Uganda.

Chaminé H.I., Barbieri M., Kisi O., Chen M. and Merkel B.J. (2018). Advances in sustainable and environmental hydrology, hydrogeology, hydrochemistry and water resources. In Proceedings of the 1st *Springer conference of the Arabian Journal of Geosciences (CAJG-1), Tunisia.*

Chapman P. M., (1995). Bioassay testing for Australia as part of water quality Assessment programmes. *Australian Journal of Ecology*, **20**(1), 7–19.

Chung E.G., Bombardelli F.A. and Schladow S.G. (2009). Modeling linkages between sediment resuspension and water quality in a shallow, eutrophic, wind-exposed lake. *Ecological Modelling* **220**, (9-10), 1251–3800. DOI : 10.1016/j.ecolmodel.2009.01.038.

Dahdouh C.Z. and Zerrouki H. (2020). Apport de la géophysique à l'étude de la structure géologique de sub-surface au sud-ouest de Djebel Sidi R'ghiss Oum El Bouaghi.

Dedić A., Gerhardt A., Kelly M. G., Stanić-Koštroman S., Šiljeg M., Kalamujić Stroil B. and Herceg N. (2020). Innovative methods and approaches for WFD: Ideas to fill knowledge gaps in *science and policy. Water Solutioin*. **3**, 30–42.

Deegan L.A., Wright A., Ayvazian S.G., Finn J.T., Golden H., Merson R.R. and Harrison J. (2002). Nitrogen loading alters seagrass ecosystem structure and support of higher trophic levels. *Aquatic Conservation: Marine and Freshwater Ecosystems*. **12**, 193–212.

Dolman A.M. and Wiedner C. (2015). Predicting phytoplankton biomass and estimating critical N:P ratios with piecewise models that conform to Liebig's law of the minimum. *Freshwater biology.* **60**, 686–697. https:// DOI: org/10. 1111/ fwb. 12518.

Downing J.A. and McCauley E. (1992). The nitrogen: phosphorus relationship in lakes *Limnology*. **37**(5). 936–945. https://DOI:10.4319/lo.1992.37.5.0936

Filatov N., Pozdnyakov D., Johannessen O.M., Pettersson L.H. and Bobylev L.P. (2005). White Sea: its marine environment and ecosystem dynamics influenced by global change. *Springer Science & Business Media.*

Gaagai A. (2009). Étude Hydrologique et Hydrochimique du bassin versant du barrage de BABAR sur Oued el ARAB région Est de l'Algérie. Doctoral dissertation. Université de Batna **2**.

Gaagai A., Boudoukha A., Boumezbeur. and Benaabidate L. (2017). Hydrochemical characterization of surface water in the Babar watershed (Algeria) using environmetric techniques and time series analysis. *International Journal of River Basin Management*. **15**(3), 361–372.

Gaagai A., Aouissi H.A. and Maalem S.E. (2021). Impact of Climate Change and Anthropic Activity on The Water Quality of Babar Dam in Algeria*. Journal of Environmental Pollution and Management*. **3**, 101.

Garizi A.Z., Sheikh V. and Sadoddin A. (2011). Assessment of seasonal variations of chemical characteristics in surface water using multivariate statistical methods. *International Journal of Environmental Science & Technology*. **8**, 581–592.

Gautam S.K., Maharana C., Sharma D., Singh A.K., Tripathi J. K. and Singh S.K. (2015). Evaluation of groundwater quality in the Chotanagpur plateau region of the Subarnarekha river basin, Jharkhand State, India. *Sustainability of Water quality and Ecology*. **6**, 57–74.

Guergazi S., Harrat N. and Achour S. (2006). Parametres Organiques et Potentiels de Formation du Chloroforme D'eaux de Surface de L'est Algerien

Gui R. and He G. (2021). The effects of internal erosion on the physical and mechanical properties of tailings under heavy rainfall infiltration. *Applied Sciences*, **11**(20), 9496.

Harlin M.M. and Thorne-Miller B. (1981). Nutrient enrichment of seagrass beds in a Rhode Island coastal lagoon. *Marine Biology*. **65**, 221–229.

Hart R.C. and Harding W.R. (2015). Impacts of fish on phosphorus budget dynamics of some SA reservoirs: evaluating prospects of 'bottom up'phosphorus reduction in eutrophic systems through fish removal (biomanipulation). *Water SA*, **41**(4), 432–440.

Hassan A.A., Dawood A.S. and AL-Mansori N.J. (2018). Assessment of water quality of Shatt Al-Basrah canal using water pollution index. *International Journal of Engineering &Technology*, **7**(4.19), 757–762.

Hossain M. and Patra P.K. (2020). Water pollution index–A new integrated approach to rank water quality. *Ecological Indicators,* **117**, 106668.

Isiuku B.O. and Enyoh C.E. (2020). Pollution and Health Risks Assessment of Nitrate and Phosphate Concentrations in Water Bodies in South Eastern, Nigeria. *Environmental Advances*, **2**: 100018

Jamali M.Z., Solangi G.S., Keerio M.A., Keerio J.A. and Bheel N., (2022). Assessing and mapping the groundwater quality of Taluka Larkana, Sindh, Pakistan, using water quality indices and geospatial tools. *International Journal of Environmental Science and Technology*, 1–14

Kalar A.R., Abas N., U.l Hasan Q., Kalair E., Kalair A. and Khan N. (2019). Water, energy and food

nexus of Indus Water Treaty: Water governance. *Water Energy Nexus* **2**:10–24.

Khadka K. and Rijal M.L. (2020). Hydrogeochemical assessment of spring water resources around Melamchi, Central Nepal. *Water Practice and Technology*, **15**(3), 748–758. https://doi.org/10.2166/wpt.2020.066

Kidou B. (2021). Population urbaine et consommation d'eau dans une region semi-aride : cas du grand Agadir (Maroc). *Geomaghreb*, (17).

Kumar A., Sharma M.P. and Yadav N.S. (2014). Assessment of Water Quality Changes at Two Locations of Chambal River: *Journal of Materials and Environmental Science*. **5** (6) 1781–1785.

Kura N.U., Ramli M.F., Ibrahim S., Sulaiman W.N.A, Aris A.Z., (2014). An integrated assessment of seawater intrusion in a small tropical island using geophysical, geochemical, and geostatistical techniques. *Environmental Science and Pollution Research*, **21,** 7047–7064.

Leclercq L. and Maquet B. (1987). Deux nouveaux indices chimiques et diatomiques de qualité d'eau courante. Application au Samson et à ses affluents (bassin de la Meuse belge). Comparaison avec d'autres indices chimiques, biocénotiques et diatomiques. *Institut Royal des Sciences Naturelles de Belgique, document de travail* **28**, 113

Liu S., Lou S., Kuang C., Huang W., Chen W., Zhang J. and Zhong G. (2011). Water quality assessment by pollution-index method in the coastal waters of Hebei Province in western Bohai Sea, China. *Marine Pollution Bulletin*. **62**(10):2220–2229.

Liu R., Chen Y., Yu W., Xu F. and Shen Z. (2016). Spatial–temporal distribution and fuzzy comprehensive evaluation of total phosphorus and total nitrogen in the Yangtze River Estuary. *Water Science and Technology*, **73**(4), 924–934.

Maberly C., Pitt J.A., Davies P.S. and Carvalho L., (2020). Nitrogen and phosphorus limitation and the management of small productive lakes. *Inland Waters*, **10**(2), 159–172.

Madene E., Boufekane A., Busico G., Meddi M. and Maizi D. (2023). Temporal evaluation of surface water quality in semiarid regions: a case study of the Ouled Mellouk dam in north-western Algeria. *Water Supply*, **23**(6), 2387–2403.

Malebo N.J. (2023). Nutritional and Functional Value of African Leafy Vegetables: Advantages and Limitations. *In Plant-Based Diet. Intech Open*.

Manahan S.E. (2010). Water chemistry: green science and technology of nature's most renewable resource. *CRC Press*.

Mass E.V. (1990). Crop Salt Tolerance KK. Tanji Ed. Agricultural Salinity Assessment and Management Manual, *ASCE New York,* 262–304.

Monography of Oum El Bouaghi province., (2009).

Nas B. and Berktay A. (2010). Groundwater quality mapping in urban groundwater using GIS. *Environmental monitoring and assessment*, **160**, 215–227.

Nikolai S.J. and Dzialowski A.R. (2014). Effects of internal phosphorus loading on nutrient limitation in a eutrophic reservoir. *Limnologica*, **49**, 33–41. DOI: 10.1016/j.limno.2014.08.005

Nixon S.W., Oviatt C.A., Frithser J. and Sullivan B. (1986). Nutrients and the productivity of estuaries and coastal and marine ecosystems. Journal*. Liminological. Society. South. Africa*. **12**, 43–71.

Nojavan A.F., Kreakie B.J., Hollister J.W. and Qian S.S. (2019). Rethinking the lake trophic state index. *PeerJ* **7**: e7936. https:// doi. org/ 10. 7717/peerj. 7936

Pacini N., Donabaum K., Henry de Villeneuve P., Konecny R., Pineschi G., Pochon Y. and Zieritz I. (2013). Water-quality management in a vulnerable large river: the Nile in Egypt. *International journal of river basin management*, **11**(2), 205–219.

Patil P.N., Sawant D.V. and Deshmukh R.N. (2012). Physico-chemical parameters for testing of water–A review. *International journal of environmental sciences*, **3**(3), 1194–1207.

Periasamy S., Subramanian P., and Surendran R. (2024). An intelligent air quality monitoring system using quality indicators and transfer learning based lightweight recurrent network with skip connection, *Global NEST Journal*, **26**(5), 06096. https://doi.org/10.30955/gnj.006096

Prathumratana L., Sthiannopkao S. and Kim K.W. (2008). The relationship of climatic and hydrological parameters to surface water quality in the Mekong River. *Environment International,* **34**, 860–866.

Putro A.S.P. (2017). Geophysical and hydrochemical approach for seawater intrusion in north semarang, Central Java, Indonesia. *GEOMATE Journal*, **12**(31), 134–140.

Quan W., Shen M.X.Q.J, Han D. and Chen Y.Q. (2005). Analysis and assessment on eutrophication status and developing trend in Changjiang estuary and adjacent East China Sea. *Mar. Environ. Sci*, **24**, 13–16.

Rosenberg D.M. and Resh V.H. (1993). Freshwater Biomonitoring and Benthic Macro invertebrates. *Chapman and Hall, New York.*

Saleem F.M. and Hussain N.A. (2013). Assessment of organic pollution levels in the northern and middle parts of Shatt Al-Arab River by applying modified organic pollution index (OPI). *Basrah Journal of Agricultural Sciences*. **26**(1).

Sargaonkar A. and 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.

Sarra EL., Aghrib N., Khadmaoui A. and Chaouch A. (2024). Ground water Quality Assessment Using Nitrate Pollution Index (NPI), in Doukkala Region Case: An Evaluative Approach. *International Journal of Chemical and Biochemical Sciences (IJCBS*), **25**(14): 412–419

Selvanarayanan R., Rajendran S., Pappa C.K. and Thomas B. (2024). Wastewater recycling to enhance environmental quality using fuzzy embedded with rnn-iot for sustainable coffee farming, *Global NEST Journal*, **26**(8), 06346. https://doi.org/10.30955/gnj.06346

Short F.T. (1987). Effects of sediment nutrients on seagrasses: literature review and mesocosm experiment. *Aquatic Botany*. **27**, 41–57.

Short F.T., Burdick D.M. and Kaldy J.E. (1995). Mesocosm experiments quantify the effects of eutrophication on eelgrass, Zostera marina. *Limnology and Oceanography*. **40**, 740–749.

Simonovic P., Simic V., Simic S. and Paunovic M. (2010). The Danube in Serbia. Republic of Serbia, Ministry of Agriculture, Forestry and Water Management–Republic Directorate for Water, University of Belgrade. Institute for Biological Research Siniša Stankovic, University of Kragujevac, *Faculty of Science.*

Simonović P.M., Paunović A., Atanack ović B., Vasiljević S., Simić A., Petrović V. and Simić. (2007). Water Quality and Assessment of the chemical and ecological status of the

Danube river and water tributaries after records from the JDS2 survey. –In: Simonović P., Simić V., Simić., Singh L.B., Pandey P.N., Mahto B., Singh R.K. 2007. River pollution.

Singh A.P., Ghosh S.K. and Sharma P. (2007). Water quality management of a stretch of river Yamuna: an interactive fuzzy multi-objective approach. *Water Resources Management,* ***21***, 515–532.

Solangi G.S., Siyal A.A., Babar M.M. and Siyal P. (2018). Evaluation of surface water quality using the water quality index (WQI) and the synthetic pollution index (SPI): a case study of Indus Delta region of Pakistan. *Desalination and Water Treatment*. **118**, 39.

Soltani A.A., Bermad A., Boutaghane H., Oukil A., Abdalla O., Hasbaia M. and Lefkir A. (2020). An integrated approach for assessing surface water quality: Case of Beni Harou dam (Northeast Algeria). *Environmental Monitoring and Assessment*, **192**, 1–17.

Supriyadi S., Purwanto P., Sarijan A., Mekuiv Y., Ustiatic R. and Prahesti R.R. (2017). The assessment of soil quality at paddy fields in Merauke, Indonesia. *Bulgarian Journal of Agricultural Science*, **23**(3).

Suresh S., Geetha Rani K., Maheswari Madhavan. and Surendran Rajendran. (2024). An Automatic Data-Driven Long-term Rainfall Prediction using Humboldt Squid Optimized Convolutional Residual Attentive Gated Circulation Model in India, *Global NEST Journal,* **26**(10), 06421. https://doi.org/ 10.30955/gnj.06421

Tang T., Zhai Y. and Huang K. (2011). Water Quality Analysis and Recommendations through Comprehensive Pollution Index Method. *Management Science and Engineering*., **5**, 95–100.

Taylor D.I., Nixon S.W., Granger S.L. and Buckley B.A. (1999). Responses of coastal lagoon plant communities to levels of enrichment: a mesocosm study. *Estuaries* **22**, 1041–1056.

Tiri A. (2010). Pollution Urbaine et Industrielle des Eaux de Surface du barrage de Koudiat Medouar Est Algerien. Thesis, *University of Batna, Algeria*.

Tokatlı C. (2014). Drinking Water Quality of a Rice Land in Turkey by a Statistical and GIS Perspective: İpsala District. *Polish Journal of Environmental Studies*, **23**(6), 2247–2258.

Turki S.A. and Maktoof A.A., (2019). Assessment of water quality for Euphrates river in AL-Nasiriyah city by using organic pollution index. *Journal of Education for Pure Science*, **9**, 58–68.

Turner R.E. and Rabalais N.N. (2003). Linking landscape and water quality in the Mississippi River basin for 200 years. *AIBS Bulletin*, **53**(6), 563–572.

Ustaoˇ glu F. and Tepe Y. (2019). Water quality and sediment contamination assessment of Pazarsuyu Stream, Turkey using multivariate statistical methods and pollution indicators. *International Soil and Water Conservation Research*. **7**, 47–56.

Venkatraman M., Surendran R., Srinivasulu S. and Vijayakumar K. (2024), Water quality prediction and classification using attention based deep differential recur flownet with logistic giant armadillo optimization, *Global NEST Journal*, **27**(1), 06799

Vila J.M., (1980). Alpine chain Eastern Algeria and the Algerian-Tunisian border, PhD Thesis in Naturel Science. *Universal. Pierre and Marie, Paris* VI.

Wetzel R.G., (2001). Limnology: lake and river ecosystem. Academic Press., *San Diego*, 1006

Yang X., Wu X., Hao H., He Z., (2008). Mechanisms and assessment of water eutrophication. *Journal of Zhejiang University Science B,* **9**(3). 197–209. https://DOI:10.1631/ jzus.B0710626

Yulianto F., Khomarudin M.R., Hermawan E., Budhiman S., Sofan P., Chulafak G.A. and Sakti A.D. (2022). Flood inundation modeling using an RProFIM approach based on the scenarios of lan duse/landcover change and return periods differences in the upstream Citarum watershed, West Java, Indonesia.

Zeinalzadeh K. and Rezaei E., (2017). Determining spatial and temporal changes of surface water quality using principal component analysis. *Journal of Hydrology: Regional Studies.* **13**, 1–10.