

# ASSESSMENT OF WATER QUALITY IN TWO DAMS IN SEMI-ARID REGION DAMS OF NORTHEASTERN ALGERIA: USING POLLUTION INDICES

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## 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<sub>2</sub> 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; Ustaoglu, 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**

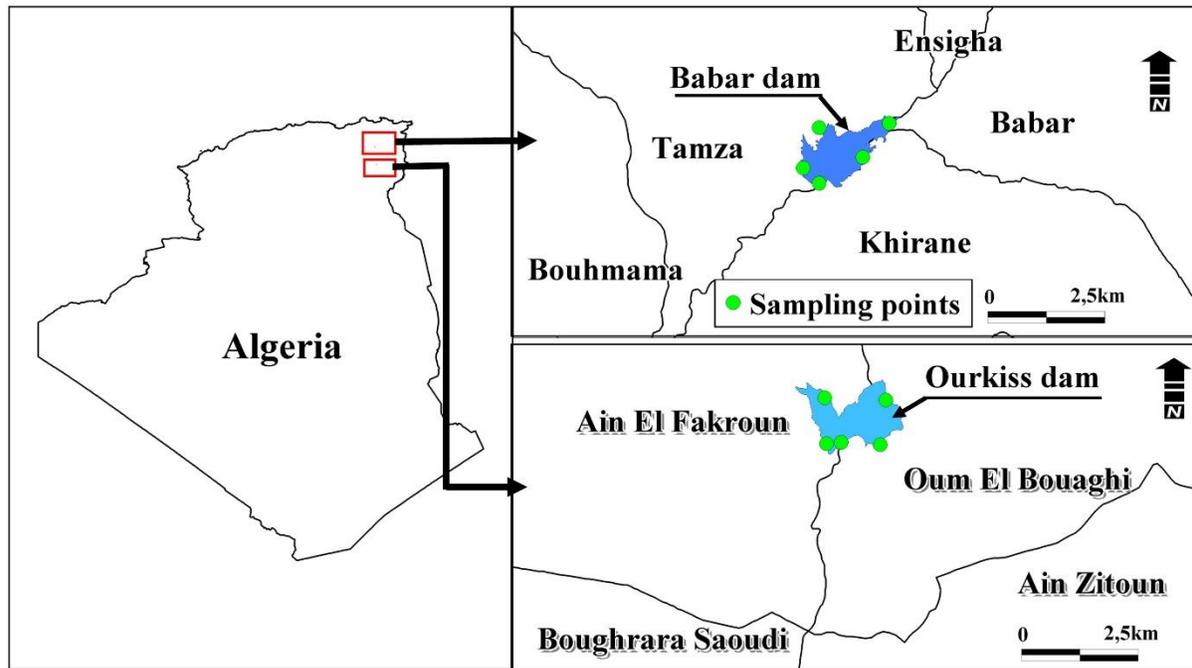
The study was conducted in the semi-arid region of northeastern Algeria, focusing on two dams located in neighboring provinces (wilayas): the Ourkiss Dam in Oum El Bouaghi and the Babar Dam in Khenchela.

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).

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 km<sup>2</sup>, 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).



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

## 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 (BOD<sub>5</sub>) were recorded in milligrams per liter (mg/L). COD was determined using the Hach DR3900 instrument, while BOD<sub>5</sub> 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<sup>-</sup>) was quantified using the argentometric method, bicarbonate (HCO<sub>3</sub><sup>-</sup> in mg/l) by arithmetic titration, and Total Hardness (TH) was determined by the CaCO<sub>3</sub> EDTA titrimetric method. Calcium (Ca<sup>2+</sup>), sodium (Na<sup>+</sup>), and potassium (K<sup>+</sup>) concentrations were analyzed through flame photometry in the laboratory.

Nitrate (NO<sub>3</sub><sup>-</sup>), nitrite (NO<sub>2</sub><sup>-</sup>), ammonia (NH<sub>4</sub><sup>+</sup>), orthophosphate (PO<sub>4</sub><sup>3-</sup>), and sulfate (SO<sub>4</sub><sup>2-</sup>) 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<sup>2+</sup>) 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),  $\text{Na}^+$ ,  $\text{K}^+$ ,  $\text{Mg}^{2+}$ ,  $\text{Ca}^{2+}$ , Bicarbonate ( $\text{HCO}_3^-$ ),  $\text{Cl}^-$ ,  $\text{NO}_3^-$ , and  $\text{SO}_4^{2-}$ . 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  $C_i$  represents the observed concentration of parameter i, and  $S_i$  denotes the standard or maximum allowable limit for that parameter. The difference between  $C_i$  and  $S_i$  is divided by  $S_i$  to assess whether there has been an increase or decrease in the parameter value (PLi) relative to its standard allowable limit ( $S_i$ ). 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)

$$PLi = \left( \frac{Ci - 7}{Si - 7} \right) \quad \text{If } PH < 7; Si = 6.5 \quad \text{If } PH > 7; Si = 8.5$$

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. (**Table1**)

**Table 1.** Classification of water quality based on WPI scores

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

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).

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 ( $K_i$ ), applying the weighting coefficient ( $W_i$ ), and deriving the synthetic pollution index (SPI).

Step1: The proportionality ( $K_i$ )

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

Step2: The weight coefficient ( $W_i$ )

$$W_i = \frac{K_i}{S_i} \quad (4)$$

Step3: The synthetic pollution index (SPI)

$$SPI = \sum_{i=1}^n \frac{C_i}{S_i} \times W_i \quad (5)$$

In this context:

$n$  represents the number of water quality parameters under analysis.

$C_i$  indicates the concentration (mg/l) of each physicochemical parameter in the sample, except pH and EC ( $\mu\text{S/cm}$ ).

$S_i$  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)

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

Range (SPI)	Type of surface water
$SPI < 0.2$	Suitable
$0.2 \leq SPI < 0.5$	Slight pollution
$0.5 \leq SPI < 1.0$	Moderate pollution
$1.0 \leq SPI < 3.0$	High pollution
$SPI \geq 3.0$	Unsuitable for drinking purposes

## 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 ( $\text{NO}_3^-$ ) and phosphate ( $\text{PO}_4^{3-}$ ) 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

### 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<sub>5</sub>, NH<sub>4</sub><sup>+</sup>, NO<sub>2</sub><sup>-</sup>, and PO<sub>4</sub><sup>3-</sup> (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**).

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

Class	BOD <sub>5</sub> (mg/ l)	NH <sub>4</sub> <sup>+</sup> (mg/ l)	NO <sub>2</sub> <sup>-</sup> (µg /l)	PO <sub>4</sub> <sup>3-</sup> (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

## 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).

**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

### 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  $(7.6 \pm 0.03)$  in the spring to  $(8.44 \pm 0.07)$  in the summer at Ourkiss dam. While at Babar Dam, pH values range from  $(7.59 \pm 0.04)$  in autumn to  $(8.03 \pm 0.05)$  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  $(966 \pm 99.12)$   $\mu\text{S}/\text{cm}$  and  $(967 \pm 99.73)$   $\text{mg}/\text{L}$  in the summer to  $(1545.67 \pm 103.84)$   $\mu\text{S}/\text{cm}$  and  $(1543.67 \pm 103.42)$   $\text{mg}/\text{L}$  in the spring. Similarly, at Babar Dam, these values range from  $(871.33 \pm 78.73)$   $\mu\text{S}/\text{cm}$  and  $(871.67 \pm 79.0)$   $\text{mg}/\text{L}$  in summer to  $(1220.67 \pm 43.57)$   $\mu\text{S}/\text{cm}$  and  $(1220.67 \pm 43.33)$   $\text{mg}/\text{L}$  in spring respectively.

Most of the water samples exhibited concentrations of  $\text{Mg}^{2+}$ ,  $\text{Cl}^-$ , and  $\text{SO}_4^{2-}$  exceeding the WHO guidelines, indicating elevated levels. At Ourkiss Dam, these values range from  $(42.92 \pm 4.05)$   $\text{mg}/\text{L}$ ,  $(247.32 \pm 20.95)$   $\text{mg}/\text{L}$ , and  $(225.08 \pm 11.39)$   $\text{mg}/\text{L}$  in summer to  $(90.96 \pm 7.69)$   $\text{mg}/\text{L}$ ,  $(337.25 \pm 10.41)$   $\text{mg}/\text{L}$ , and  $(335.47 \pm 18.78)$   $\text{mg}/\text{L}$  in spring. For Babar Dam, the corresponding values are  $(39.71 \pm 5.58)$   $\text{mg}/\text{L}$ ,  $(142 \pm 13.25)$   $\text{mg}/\text{L}$ , and  $(279.69 \pm 40.46)$   $\text{mg}/\text{L}$  in summer, and  $(110.61 \pm 12.40)$   $\text{mg}/\text{L}$ ,  $(295.83 \pm 18.84)$   $\text{mg}/\text{L}$ , and  $(471.43 \pm 42.70)$   $\text{mg}/\text{L}$  in spring, respectively.

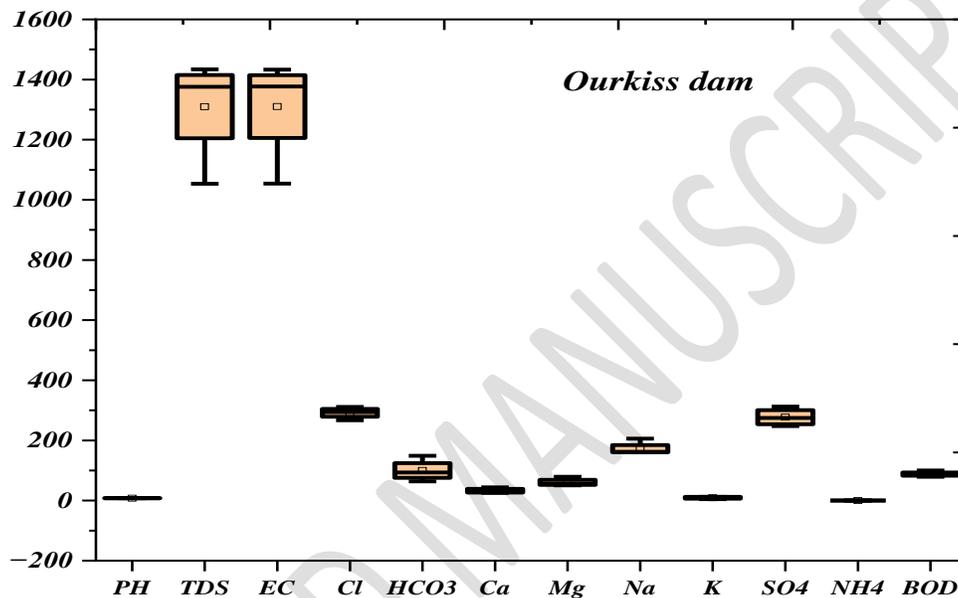
Calcium ( $\text{Ca}^{2+}$ ), Sodium ( $\text{Na}^+$ ), and Potassium ( $\text{K}^+$ ) levels were generally within the World Health Organization (WHO) limits, with a few exceptions. Sodium exceeded the recommended limits at both reservoirs during the spring, and potassium exceeded the limits at Ourkiss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

Concentrations of Nitrites ( $\text{NO}_2^-$ ), Ammonium ( $\text{NH}_4^+$ ), Orthophosphates ( $\text{PO}_4^{3-}$ ), and Nitrates ( $\text{NO}_3^-$ ) 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 ( $0.73 \pm 0.16$  mg/L) and at sites 3 ( $0.45 \pm 0.09$  mg/L) and 4 ( $0.60 \pm 0.09$  mg/L) in the autumn. Similarly, at Babar Dam, site 3 showed an exceedance in summer ( $0.46 \pm 0.04$  mg/L), and sites 1 ( $0.42 \pm 0.03$  mg/L) and 2 ( $0.45 \pm 0.03$  mg/L) in the autumn also surpassed the limit.

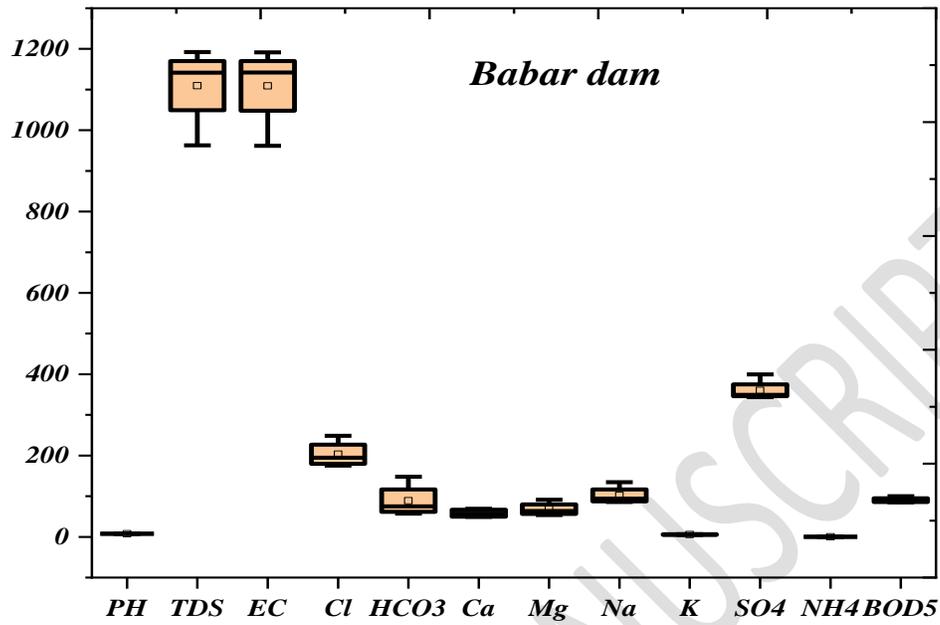
Biodegradability was assessed using biochemical oxygen demand ( $\text{BOD}_5$ ). At Ourkiss Dam,  $\text{BOD}_5$  values ranged from ( $76.92 \pm 1.46$ ) mg/L to ( $102.34 \pm 1.39$ ) mg/L, while at Babar Dam, they ranged from ( $82.45 \pm 1.78$ ) mg/L to ( $103.70 \pm 1.39$ ) mg/L. These values far exceeded the WHO standard range of (2–20) mg/L. The annual mean  $\text{BOD}_5$  value was estimated at ( $89.58 \pm 9.66$ ) mg/L at Ourkiss Dam and ( $90.30 \pm 4.86$ ) mg/L at Babar Dam during the 2023–2024 period, both exceeding the WHO limit.

Previous studies on the Babar Dam (Gaagai, 2017) have shown that the parameters exceeding the limits set by WHO standards namely, EC, TDS,  $\text{Cl}^-$ , and  $\text{SO}_4^{2-}$  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,  $\text{Cl}^-$ , and  $\text{SO}_4^{2-}$ .

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



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

**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 <sup>-</sup>	HCO <sub>3</sub> <sup>-</sup>	TH	Ca <sup>2+</sup>	Mg <sup>2+</sup>	Na <sup>+</sup>	K <sup>+</sup>	SO <sub>4</sub> <sup>2-</sup>	NH <sub>4</sub> <sup>+</sup>	NO <sub>2</sub> <sup>-</sup>	NO <sub>3</sub> <sup>-</sup>	PO <sub>4</sub> <sup>3-</sup>	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
	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
Summer	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
	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
Autumn	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
	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
	Winter	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
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 ( $\mu$  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 <sup>-</sup>	HCO <sub>3</sub> <sup>-</sup>	TH	Ca <sup>2+</sup>	Mg <sup>2+</sup>	Na <sup>+</sup>	K <sup>+</sup>	SO <sub>4</sub> <sup>2-</sup>	NH <sub>4</sub> <sup>+</sup>	NO <sub>2</sub> <sup>-</sup>	NO <sub>3</sub> <sup>-</sup>	PO <sub>4</sub> <sup>3-</sup>	BOD <sub>5</sub>	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

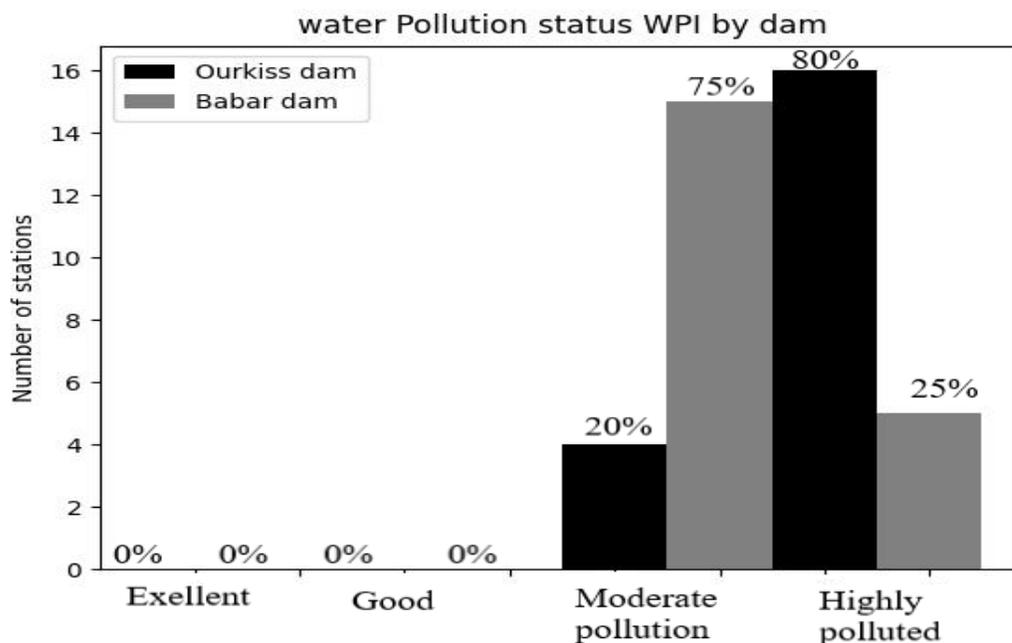
All values (Means) are in mg/l except PH and EC ( $\mu$  Siemens/cm), SD: standard deviation, SP: Spring; SU: Summer; AU: Autumn; WI: Winter; B: Babar dam.

### 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 ( $1.19 \pm 0.06$ ), while the lowest value was observed at site 3 in summer ( $0.82 \pm 0.06$ ), 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.

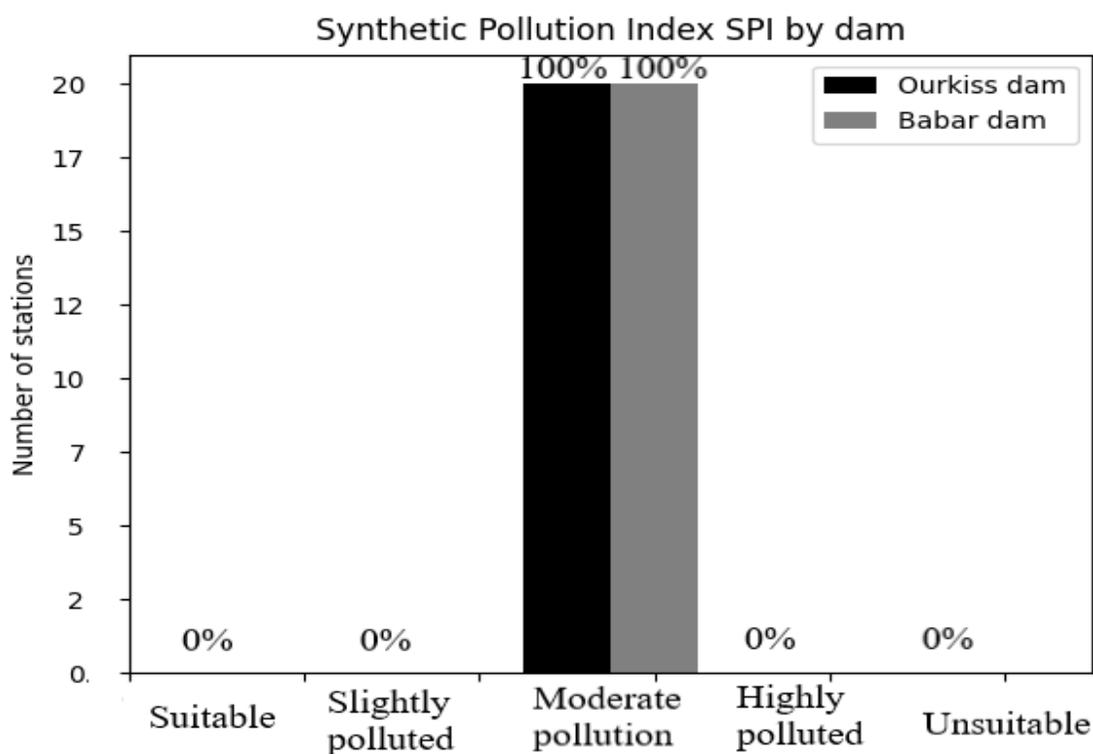
At Babar Dam, the highest WPI value was recorded at site 5 in spring ( $1.17 \pm 0.09$ ), and the lowest at site 5 in summer ( $0.74 \pm 0.09$ ). The annual average WPI for Babar Dam was 0.94, placing it in the "moderate pollution" category. Water quality at Babar Dam was classified as "Highly Polluted"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



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

### 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  $(0.72 \pm 0.06)$  to  $(0.92 \pm 0.06)$ , while at Babar Dam, the SPI varied from  $(0.67 \pm 0.04)$  to  $(0.86 \pm 0.04)$ .



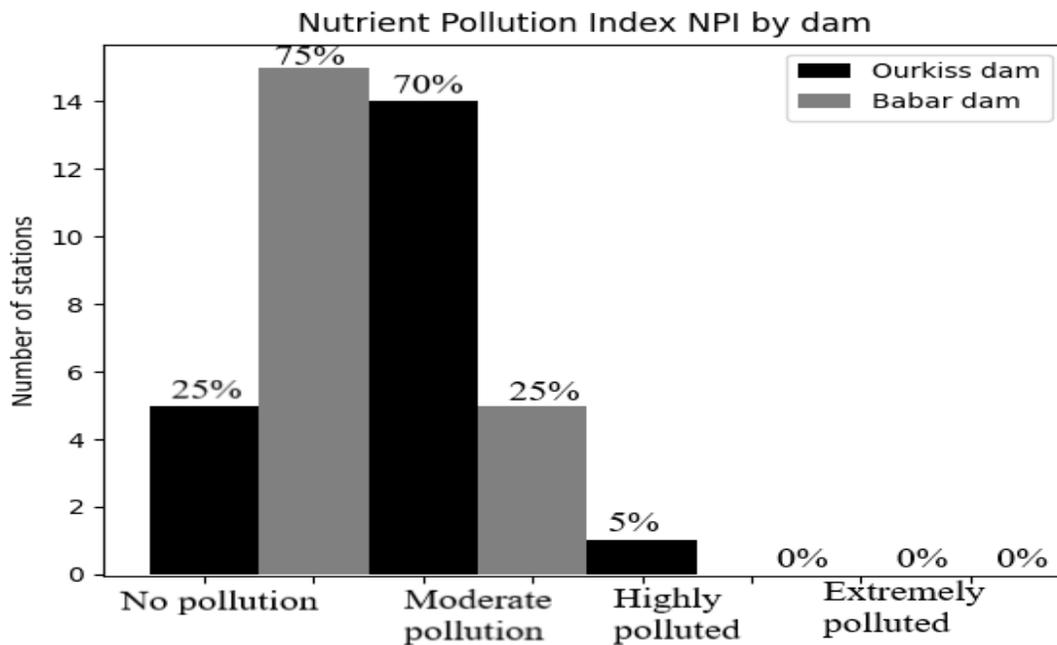
**Figure 5.** Synthetic Pollution Index (SPI) for the Ourkiss and Babar Dams during the four seasons.

### 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 ( $1.4 \pm 0.56$ ). 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).

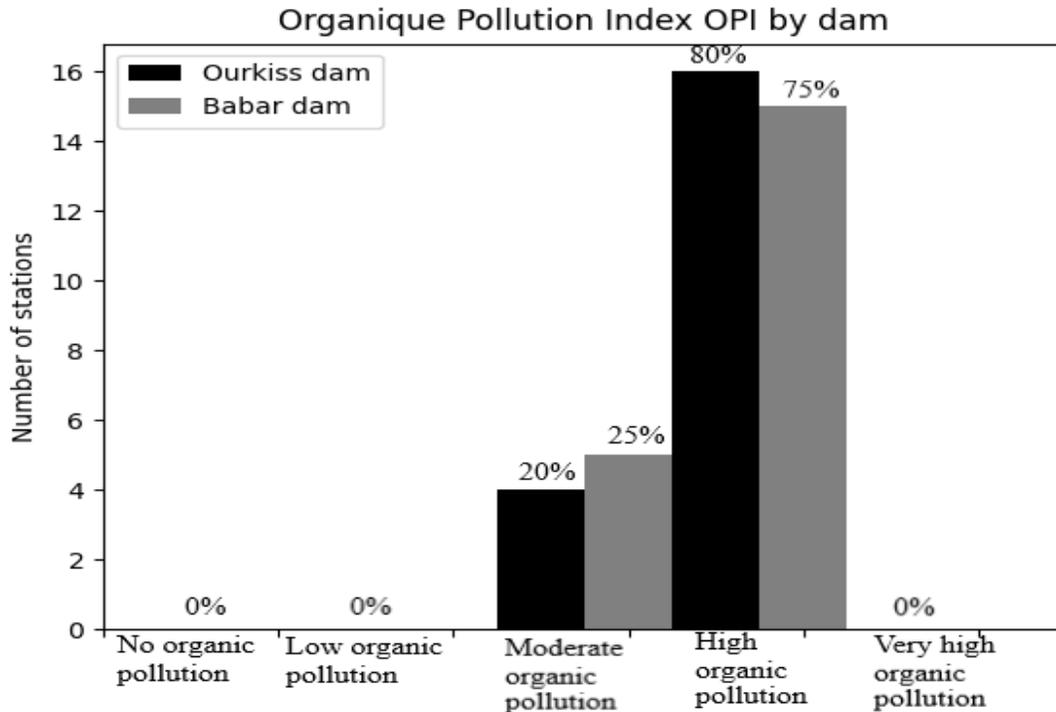


**Figure 6.** Nutrient Pollution Index (NPI) for the Ourkiss and Babar Dams during the four seasons.

### 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  $(3 \pm 0.22)$ . 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  $(3 \pm 0.22)$ . 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  $(2.25 \pm 0.22)$  to  $(2.75 \pm 0.22)$  across both dams (**Figure 7**).

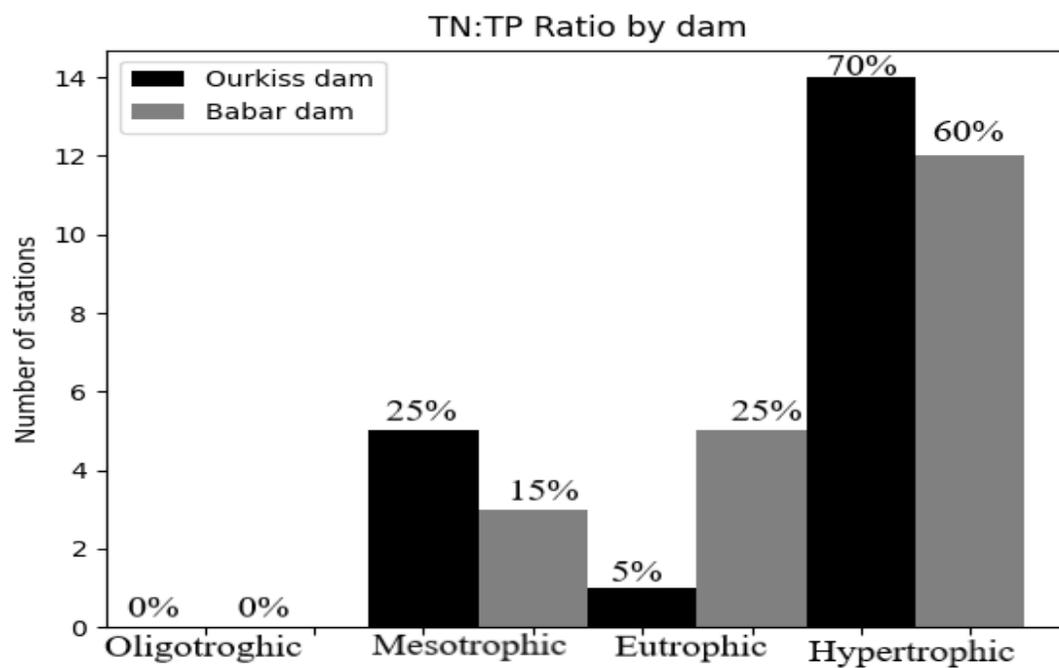


**Figure 7.** Organic Pollution Index (OPI) of the two dams (Ourkiss and Babar).

### 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  $(83.98 \pm 8.83)$ , 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  $(5.15 \pm 1.38)$ , 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  $(65.47 \pm 31.79)$ , 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  $(7.73 \pm 4.04)$ , 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.

### 3. 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  $(1109.53 \pm 72.30)$  mg/l and  $(1109.23 \pm 72.77)$   $\mu\text{S}/\text{cm}$ , respectively, while the Ourkiss Dam had higher values of  $(1309.92 \pm 141.12)$  mg/l and  $(1310.2 \pm 141.15)$   $\mu\text{S}/\text{cm}$ .

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 ( $\text{Cl}^-$ ) in Ourkiss Dam exceeded the WHO's safe limit of 250 mg/l for drinking water, with an annual mean concentration of  $(292 \pm 23.4)$  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  $\text{SO}_4^{2-}$ , primarily due to the presence of evaporite formations in the area. Additionally, wastewater discharge from urban sectors contributes to increased  $\text{SO}_4^{2-}$  levels (Kura, 2014). The extensive use of sulfate fertilizers in intensive agriculture further elevates  $\text{SO}_4^{2-}$  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.

$\text{Mg}^{2+}$  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,  $\text{BOD}_5$ , 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  $\text{BOD}_5$  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  $\text{BOD}_5$  values (Prathumratana et al., 2008). The highest  $\text{BOD}_5$  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.

#### **4. 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  $\mu\text{S}/\text{cm}$  in Ourkiss and 855 to 1251  $\mu\text{S}/\text{cm}$  in Babar. TN and TP concentrations exceeded the World Health Organization standards. Additionally,  $\text{Mg}^{2+}$  levels surpassed 90 mg/L in Ourkiss and exceeded 110 mg/L in Babar during certain seasons. Similarly,  $\text{SO}_4^{2-}$  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.

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