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Time series analysis and modeling of physicochemical water parameters in Ghrib dam, Medea, Algeria

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ABSTRACT

The preservation of aquatic ecosystems largely depends on water quality. In this context, the analysis focuses on the evaluation and modeling of the water quality of the Ghrib dam, located in the wilaya of Medea, characterized by marked seasonal variations. The main objective is based on the analysis of six quality indicators: water temperature (TW), dissolved oxygen (DO_2), PH, nitrates (NO_3), turbidity (TUR), and organic matter (OM), in order to better understand their temporal dynamics and predict their future developments. The data were collected over a period (2018–2024), and then ARIMA (Autoregressive Integrated Moving Average) models were developed to model the temporal trends and provide 24-month forecasts. The stationarity test was verified by the Dukey-Fuller (ADF) test, validating the application of the ARIMA model for each parameter. The results of the ARIMA model demonstrate a good ability to capture the trend with satisfactory performance indicator values and offer reliable forecasts over 24 months with appropriate confidence intervals. This study provides a solid foundation for ensuring good water quality monitoring and contributes to the development of an adapted water resource management strategy considering natural and anthropogenic pressures.

Keywords: ARIMA, Ghrib dam, ARIMA model, water quality, Medea.

INTRODUCTION

Water, a vital commodity on Earth, is a recyclable resource. It is essential for the development of all areas of human effort (Obi et al., 2006; Merrah, 2010). Nevertheless, because it is highly vulnerable to pollution and overexploitation, active management and protection are essential (Osuolale and Okoh, 2017). Water quality is a major issue in life due to its direct impact. Impact on human health. Water quality could be affected by geological structure, salinity, overexploitation of groundwater, the entry of urban and domestic wastewater into watercourses, as well as agricultural drainage and a wide range of chemical compounds (Tsakiris and Alexakis, 2012).

Uncontrolled urbanization in developing countries frequently leads to anthropogenic water pollution, as wastewater is often discharged directly into the environment without proper treatment (Youmbi et al., 2013).The pollutants in these discharges chemically and physically degrade surface waters, a process that in many instances causes a loss of aquatic biodiversity (Emmanuel et al., 2009).effective evaluation of water quality, which is determined by its biological,-physical,and chemical properties, hinges on three critical steps: data interpretation, modelling, and classification (Bayacioglu, 2006).

The analysis of time series data offers a powerful approach to both understand complex processes and predict future states based on historical information.in natural aquatic systems, examining long-term water quality trends reveals meaningful patterns of chemical and biological variation. This patterns of change largely result from seasonal influences, human intervention, or a combination thereof. The success of this type of trend analysis largely depends on the initial exploration data analysis and the identification of appropriate model orders to predict the trend (Hipel, 1985). Hydrologists have increasingly developed and employed mathematical models for hydrology and water quality in recent years. These tools are essential for planning, resource management, and predicting how altered conditions will impact water quality (Ziemińska-Stolarska and Skrzypski, 2012; Loucks and Beek, 2017; Liu, 2018; Olowe, 2018; Mbuh et al., 2019; Najafzadeh et al., 2021).

The main methods for predicting water quality are the time series model and the deep learning model. Time series analysis is based on the study of the historical characteristics of a given variable. Next, a model is constructed based on its regularity to predict the state or value of the variable in the following period. Due to its flexibility, simplicity, and feasibility, the integrated autoregressive model the integrated autoregressive moving average model (ARIMA) has become the most important and widely used time series model (Box et al., 1994; Chen, 2007; Faruk 2010; Hanh, 2010; Voudouris et al., 2010, Jatinder et al., 2023, Dinna et al., 2019). Time series forecasting is carried out with the help of ARIMA. In the ARIMA model, AR stands for autoregression, and MA stands for moving average. In ARIMA, the non-seasonal part is represented by (p, d, q) where p is the number of autoregressive values, d is the order of differencing, and q is the number of moving average values. Several studies conducted on the modeling of time series of water parameters include (Salas et al.,1982; Weeks et al., 1987; Tizro et al., 2014; Ghashghaie et al., 2018; Mirsanjari and Mohammadyari 2018; Zhang et al., 2016; Zhang, 2003; Qi An and Min Zhao, 2017; Wahid and Arunbabu, 2022; Katimon et al., 2017; Zafra-Mejía et al., 2024; Irvine et al., 1992; Papamichail et al., 2001; Padilla et al., 1996; Montanari et al., 2000; Zafea-Mejia, 2024). Algeria is located in one of the most disadvantaged regions of the world in terms of water availability. However, not only does the population explosion and economic growth lead to a demand for water that far exceeds the available resources, but, moreover, nothing indicates that the drought that has persisted over the past two decades will give way to abundant rainfall (Loucif-Seiad, 2002). Knowledge of the different types of aquatic environments and their functions is essential for better detecting pollution and understanding its ecological consequences (Bonnard et al., 2003). To meet this challenge, water quality modeling tools can be particularly useful. They are both necessary to describe and predict water quality conditions and to understand the functioning of the aquatic ecosystem. (Riahi, and St-Hilaire, 2023). The objective of this study is to evaluate the temporal variability of the main physicochemical parameters of water and to model the time series of each parameter using ARIMA models to capture the temporal dynamics and thus predict the future evolution of water quality at the Ghrib dam.

MATERIALS AND METHODS

Study area

The Ghrib Dam is located in the Cheliff Valley, 7 km upstream from the center of Oued Cheurfa, 45 km from Khemis Meliana, 30 km southwest of Medea, and 150 km west of Algiers. Upstream of Ghrib, the Cheliff is regulated by the Boughzoul dam, which is located 20 km south of Boughari and 110 km from Ghrib, with a longitude of 02°35’1400” E and a latitude of 36°07’5290”N. The Ghrib dam is located at a longitude of 02°35’14 00” E and a latitude of 36°07’52 90” N; Z=450 (ANBT, 2008) (Figure 1).

Data collection

The data for our study on the water quality of the Ghrib dam were meticulously collected from a comprehensive database containing the main parameters. The data collected reliably and authorized from the monitoring station of the studied dam (ADE, Ghrib), for a period extending from 2018 to 2024, constitute a solid foundation for our study. A substantial amount of historical data is necessary to identify trends and long-term changes in the water quality of the studied dam,

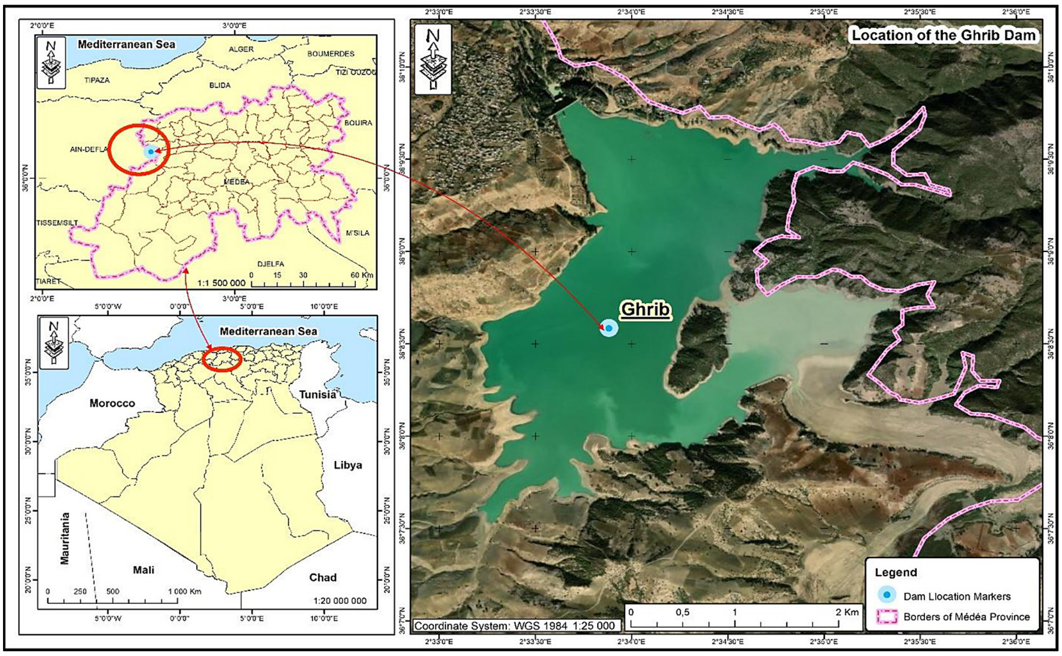

Figure 1. Geographic location of the Ghrib dam

as well as to conduct in-depth analyses of the ecological health of the dam, thereby informing and shaping effective policy decisions and management strategies. The dataset includes 13 physicochemical parameters such as Temperature (TW in °C), PH, electrical conductivity (EC in µS/cm), nitrate (NO_3 in mg/l), chloride (Cl^- in mg/l), calcium (Ca^{+2} in mg/l), organic matter (OM in mg/l, turbidity (TUR in NTU), dissolved oxygen (DO_2 in mg/l), phosphates (PO_4 in mg/l), biochemical oxygen demand (BOD_5 in mg/l), and chemical oxygen demand (COD in mg/l).

Analytical method

The analysis of the parameters was carried out according to the protocol described by Rodier (1984) (Table 1).

Table 1. Analytical methods of the parameter of water

Parameters	Methods
TW, PH, CE	in-*situ* measurement (HACH SL1000)
DO_2	Oxymeter (HACH HQ1130)
OM, PO_4, DCO, NO_3	Colorimétric analysis using spectrophotometer (HACH DR/2000)
BOD5	DBO meter (Oxi WTW).
Cl^-	Titrimétric method by AgNO3
$Ça^{+2}$	Titrimétric method by EDTA
TUR	Turbidimeter (HACH 2100N)
DR	Gravimetric methods

Statistical analysis

In this study, six physicochemical parameters were selected: TW, DO_2, OM, PH, NO_3, and TUR. To characterize the temporal variations of these parameters, descriptive statistical analyses were conducted on all the parameters to extract the trend of each parameter over the study period and thus evaluate the relationships between them.

All the time series were modeled using an ARIMA approach to identify trends and random components that which allows for the forecasting the water quality of the Ghrib dam (Figure 2). All analyses were conducted using the R software (CRAN version, 2024).

Augmented Dickey-Fuller Test ADF – before applying ARIMA models, it is necessary to conduct a stationarity test on our time series, as a stationary series possesses constant statistical properties. To verify this property, we applied an Augmented Dickey-Fuller (ADF) test, which allows us to determine the presence of a unit root in our series.

The ADF (1981) is a unit root test that allows us to verify whether a series is stationary or not (Dickey Fuller, 1981).

The hypotheses of the ADF test are defined as follows; A non-stationary process will correspond to one of the following forms of non-stationarity:

$$\Delta x_t = \emptyset x_{t-1} + \sum_{i=1}^{p} \alpha_i \, \Delta x_{t-i} + \epsilon_t \; \emptyset = \rho - 1 \quad (1)$$

$$\Delta x_t = \alpha + \emptyset x_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta x_{t-i} + \epsilon_t \quad (2)$$

$$\Delta x_t = \alpha + \beta t + \emptyset x_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta x_{t-i} + \epsilon_t \quad (3)$$

where: Δ_t – first difference of the series; x_{t-1} – lagged value of the series; $\emptyset$ – parameter tested for stationarity; ϵ_t – error term; ρ – autoregressive coefficient; α_i – coefficients of lagged differences; βt – deterministic trend term.

The hypotheses to be tested are:

- H0: The series is not stationary (existence of a unit root).
- H1: The series is stationary (absence of a unit root).

In R, the Augmented Dickey-Fuller (ADF) tests are implemented in the functions. The function adf.test () in the tseries package. If the P-value is less than the significance level (0.05), we say that the series is stationary. And when the ADF test reveals non-stationarity, a differentiation of the data was carried out to stabilize the means (Loudjani, 2022). ARIMA is a model that analyzes data over time to predict future trends. It uses an analysis method to try to predict future movements by looking at the differences between values instead of relying on the actual values of the data. Differenced series have lags called "autoregressive" and the lags of the predicted data are called "moving average." This model is represented by ARIMA (p, d, q), where (p) represents the order of autoregression, (d) shows the degree of differencing, and (q) shows the order of the moving average.

The inclusion of autoregressive and moving average processes is more favorable for achieving greater flexibility in real time series data, which begins with the combination of autoregressive and moving average processes designated by ARMA (p.q.). ARMA (p.q) is indicated by:

$$\emptyset(B)\gamma t = \theta(B)\varepsilon t \quad (4)$$

$$\emptyset(B) = 1 - \emptyset 1B - \emptyset 2B^2 - \cdots \ldots \emptyset_\rho B^P \quad (5)$$

$$\theta(B) = 1 - \theta 1B - \theta 2B^2 - \cdots \ldots - \theta_q B^q \quad (6)$$

where: B – the bachshift operator express by B $(Y_t) = Y_{t-1}$, P – order of AR, q – order of MA (Gowthaman et al., 2022).

RESULTS AND DISCUSSION

Statistical summary

The descriptive analysis of the physicochemical parameters highlighted distinct characteristics for each parameter. The waters of the Ghrib dam are slightly alkaline with an average value of 8.06. The average temperature is 18.79, varying between 8.80 and 28.1, which reflects seasonal fluctuations. The average value of organic matter is 4.9 mg/l, with moderate variability (SD = 1.93), indicating potential variations in organic inputs.

The average turbidity value is 9.9 NTU with a high standard deviation (SD = 4.16), which could be a sign of events with high particulate load. The waters of the Ghrib dam show significant oxygenation with an average of 8.65 mg/l. Nitrate concentrations show significant fluctuations with an average of 2.78 mg/l, suggesting inputs related to agricultural activities, while phosphates remain consistently low with an average of 0.55 mg/l, with recorded peaks reaching 3.96 mg/l. The recorded values are similar to those reported by Hamil et al., (2018); Halouz et al., (2021); Soltani et al., (2022). The biochemical oxygen demand BOD_5 is established at 4.14 mg/l, indicating a moderate organic load. The high value of electrical conductivity with an average (2506 µS/

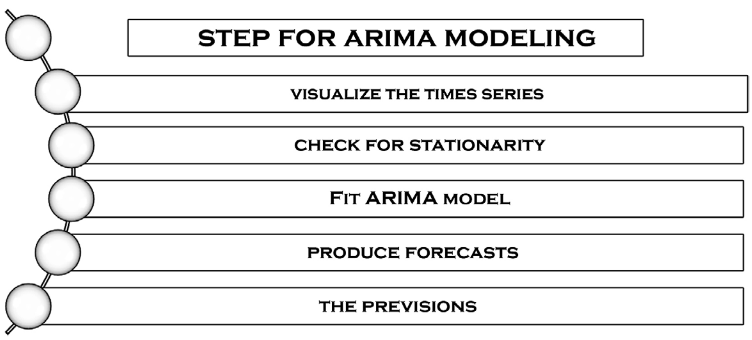

Figure 2. The steps of the ARIMA model

cm) is associated with significant concentrations of chlorides (356.86 mg/l) and calcium (155.53 mg/l), indicating a significant mineralization of the water. The chemical oxygen demand (COD) reveals a variation in the oxidizable load, with an average of 17.44 mg/l (Table 2).

PCA and correlation matrix

Principal component analysis (PCA) applied to all physicochemical parameters shows a total inertia rate of 56.3%. The first axis (dim1) explains 37% of the total variance and the second axis (dim2) explains 19.3% of the total variance. According to the PCA correlation circle (Figure 3), it is observed that axis 1 is mainly associated with the parameters indicating mineralization CE, DR, CL^-, Ca^{+2}, which indicates that these parameters influence water quality. Axis 2 is related to biological and organic parameters (BOD5, COD, OM), which are strongly positively correlated with each other. While PO_4, NO_3 and DO_2 have a weak contribution.

The correlation matrix (Figure 3) highlights the linear relationships between the physicochemical parameters of the water. A positive

Table 2. Results of descriptive analysis of the physicochemical parameters of water

Parameters	Mean	Median	SD	SE	Min	Max
PH	8.06	8.31	0.61	0.08	6.58	8.76
TW	18.79	18.50	6.25	0.81	8.80	28.1
OM	4.9	4.85	1.93	0.25	2.20	12.5
TUR	9.9	8.88	4.16	0.54	4.39	29
DO_2	8.65	8.12	2.12	0.27	5.64	12.91
NO_3-	2.78	2.65	1.92	0.25	0	7.90
PO_4-	0.55	0.04	0.88	0.12	0	3.96
BOD5	4.14	3	2.39	0.32	1	10
CE	2506.52	2395	630.81	81.44	1472	3820
DR	1553.57	1556	556.44	71.84	598	2539
Cl^-	356.86	327.95	100.53	12.98	183.4	541.3
Ca^{+2}	155.53	157	29.7	3.83	96	211
DCO	17.44	18.50	8.74	1.17	5	54

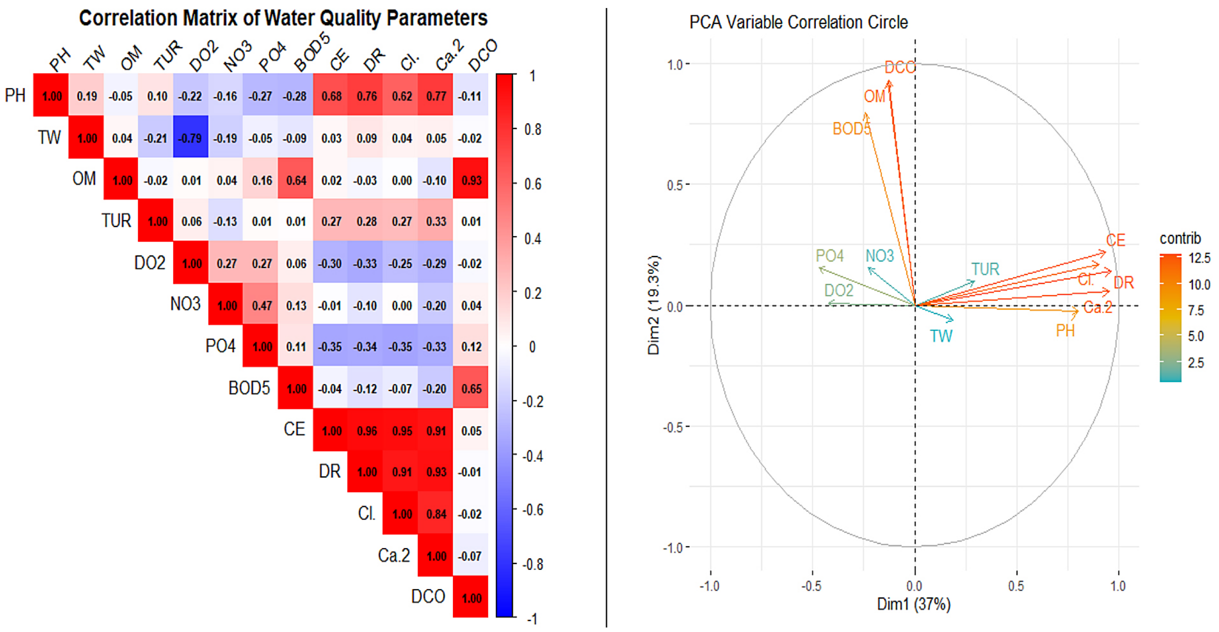

Figure 3. Multidimensional analysis of the water quality of Ghrib Dam (PCA + correlation matrix)

correlation is observed between electrical conductivity (EC) and total dissolved solids (r=0.91), calcium (r=0.93), and chlorides (r=0.84). Thus, there is a positive correlation between organic matter and BOD (r=0.93) The water temperature is negatively correlated with dissolved oxygen (r=-0.79), indicating a decrease in oxygen solubility in warm water.

Trend analysis

The analysis of the time series of physicochemical parameters over the period 2018–2024 highlights remarkable seasonal fluctuations. (Figure 4). The dissolved oxygen (DO_2) exhibited marked seasonal variations, characterized by recurring annual peaks. Its evolution appears relatively stable, with slight fluctuations around a constant average. The concentrations of nitrates (NO_3) show a positive trend over the studied period. Suggesting a potential increase in anthropogenic inputs with the presence of seasonal fluctuations. The organic matter (OM) content showed a negative trend despite occasional peaks. A seasonal variability in pH values and a positive trend before 2022, followed by stabilization. The temperature (TW) and turbidity (TUR) also show notable seasonal variations. With isolated peaks of turbidity recorded that could result from runoff events. Moreover, the temperatures follow an expected annual cycle with elevated values in summer and low values in winter. The results of the stationarity test applied to the monthly values of the physicochemical parameters to verify the stationarity of the data and after differencing (Table 3) indicate that our time series is stationary (P-value<0.05).

The analysis of the time series of the six water quality indicators was carried out using the ARIMA model. We used an ARIMA (1,0,0)(0,0,1)

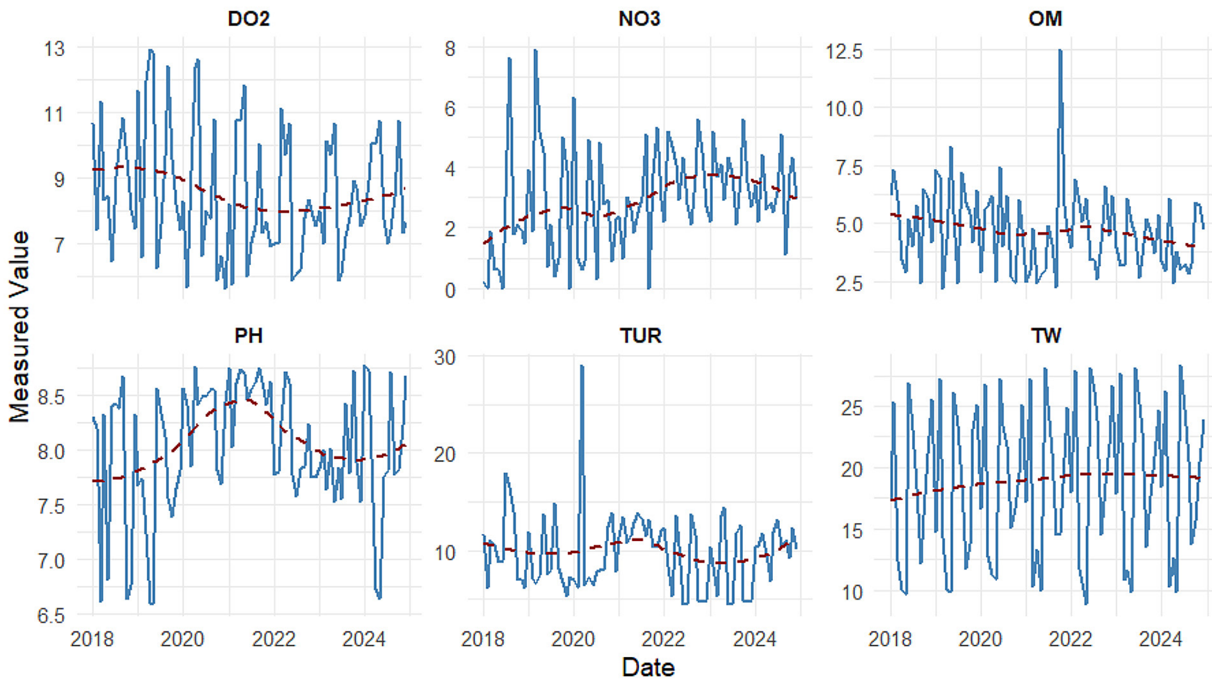

Figure 4. Temporal evolution of water quality parameters (2018–2024)

Table 3. Results of stationarity test (ADF)

Parameters	Stat ADF	P-value	Initial stationarity	P-value after differencing
TW (°C)	–7.31	< 0.01	Stationnary	0.01
PH	–2.54	0.354	Non -stationary	0.01
DO_2 (mg/L)	–4.99	< 0.01	Stationary	0.01
Turbidity (NTU)	–3.82	0.0217	stationary	0.0217
OM (mg/L)	–3.81	0.0226	stationary	0.0226
NO_3 (mg/L)	–4.72	< 0.01	Stationnary	0.01

Table 4. ARIMA model performance metrics

Parameters	Final ARIMA model	Coefficients	AIC	RMSE	MAE	MAPE (%)	ACF_1 of the residuals
TW (°C)	ARIMA (1, 0,0) (0, 0,1) [12]	AR1 = 0.30, SMA1 = 0.30	145.67	0.545	0.434	5.57	0.007
PH	ARIMA (0, 1,1)	MA1 = –0.96	338.44	1.78	1.40	36.96	–0.058
DO_2 (mg/L)	ARIMA (1, 0,0) (0, 1,0) [12]	AR1 = 0.36	245.24	1.20	0.81	9.73	0.001
Turbidity (NTU)	ARIMA (3, 1,0)	AR1 = –0.63, AR2 = –0.58, AR3 = –0.35	481.54	4.15	2.92	33.97	–0.053
OM (mg/L)	ARIMA (0, 1,1)	MA1 = –0.96	338.44	1.78	1.40	36.96	–0.058
NO_3 (mg/L)	ARIMA (0, 1,1)	MA1 = –0.93	332.81	1.72	1.25	— (zero values)	–0.021

Note: AIC – Akaike information criterion, MAPE – mean absolute percentage error, RMSE – root mean square error, MAE – mean absolute error, ACF – autocorrelation function.

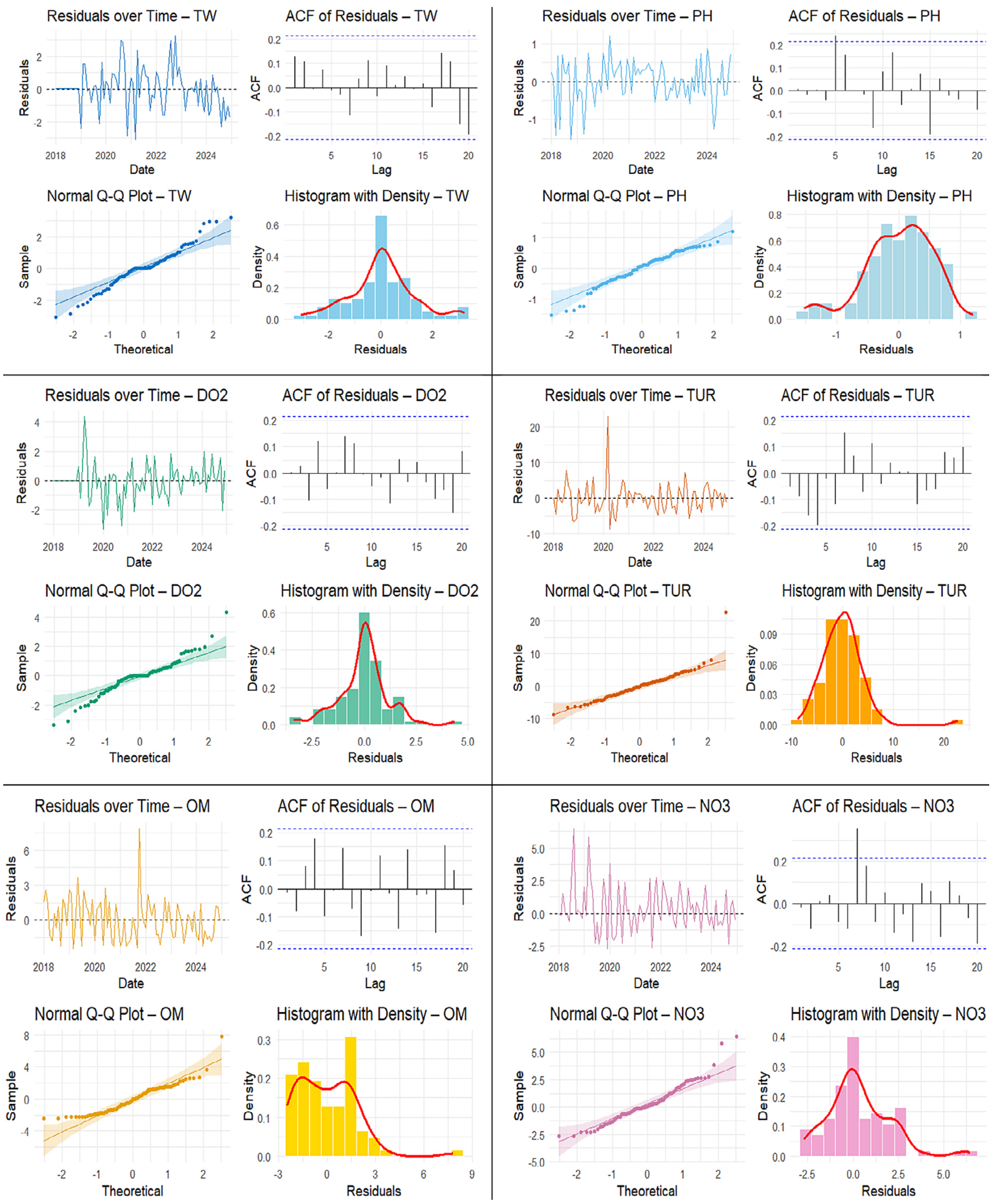

Figure 5. Results of the analysis of the residuals of the studied parameters

[12] model to model the water temperature (TW), which takes into account an autoregressive term and a seasonal component, allowing us to effectively capture the annual variations with a MAPE of 5.77%, and our model's performance indicators are satisfactory (AIC = 145.67%, RMSE = 0.545). For the pH, a first-order differencing was necessary using an ARIMA (0, 1, 1) model, which includes a significant moving average term (MA1 = -0.96); however, this prediction is less accurate with a MAPE = 36.96%. The ARIMA (1, 0, 0) (0, 1, 0) [12] model was successfully used to model, taking into account seasonality and showing a good fit with a MAPE = 9.73%. Regarding turbidity (TUR), we opted for the ARIMA (3, 1, 0) model incorporating numerous

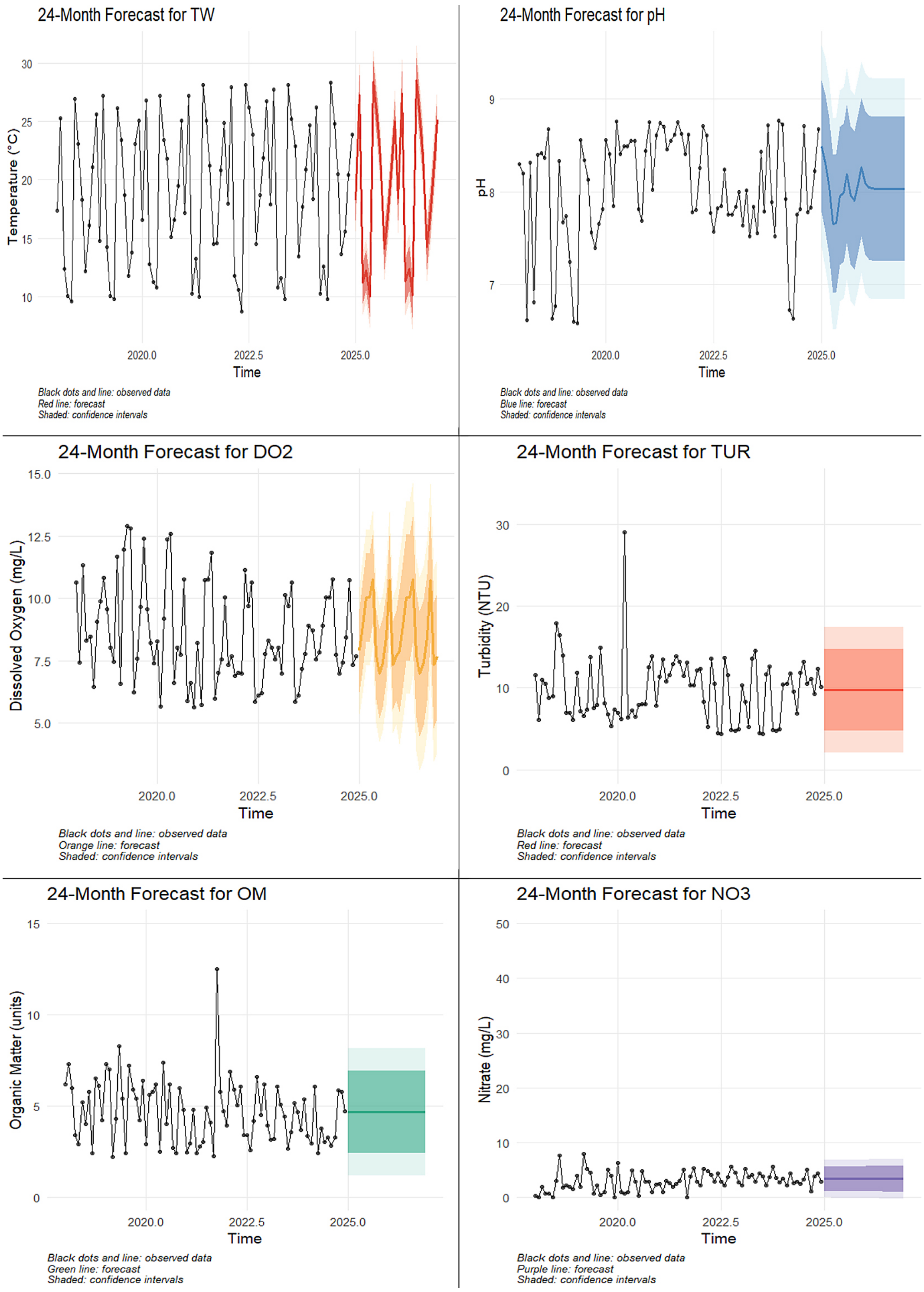

Figure 6. The 24-month forecasts for each parameter

autoregressive terms, despite the error rate being relatively high (MAPE = 34%). ARIMA (0, 1, 1) models were used to model organic matter (OM) and nitrates (NO_3) with terms close to -0.96 and -0.93 respectively, although the average errors are moderate (Table 4). All the models show a low residual autocorrelation, indicating that the chosen ARIMA models are well-fitted and suitable for describing the temporal dynamics of the analyzed parameters.

Residual analysis

To evaluate the goodness of fit of the models and the relevance of the modeling of our time series, it is necessary to perform a residual analysis for the different parameters studied.

The diagrams show that the residuals are distributed around zero without a marked trend. This means that the model captures the central dynamics of the data well. The autocorrelation function (ACF) plots show that most values are close to zero for most lags, which confirms the independence of the residuals (Figure 4). The QQ-plot graphs indicate that the residuals generally exhibit a normal distribution, a fundamental criterion to confirm the assumption of error normality. The histogram with density confirms the symmetry of the residuals. These results show that our ARIMA model is adequate for capturing the trends and seasonality of the physicochemical parameters of the water from the Ghrib dam.

The forecasts

According to Figure 5, we observe that the forecasts for water temperature (TW) show a remarkable seasonal variation with oscillations expected around current levels, reflecting the natural seasonal dynamics of aquatic environments. The confidence interval remains narrow, indicating a good accuracy of our model. While the predicted PH values remain stable around 8, suggesting a chemical stability of the reservoir waters during the studied period. The values of dissolved oxygen (DO_2) show a constant evolution with slight seasonal fluctuations, which means that aquatic life remains favorable. Turbidity also shows relatively stable concentrations, with predicted values centered around current values. The forecasts for organic matter (OM) show a slight decrease, while the levels of nitrates (NO_3) seem to stabilize, with a slight positive trend.

CONCLUSIONS

This study aims to analyze and evaluate the quality of the Ghrib dam waters through six indicators: water temperature (TW), PH, dissolved oxygen (DO_2), nitrates (NO_3), turbidity (TUR), and organic matter (OM). The results obtained reveal a notable seasonal fluctuation of certain parameters, such as TW and DO_2, while the pH maintained a certain stability. Turbidity and organic matter showed moderate variations reflecting anthropogenic effects or natural events. Moreover, the increase in nitrate levels highlights a potential pressure on nutrient input. The application of the ARIMA model to our data ensures reliable predictions of future trends of these parameters over a period of 24 months. The performance indicators of our model (MAE, MAPE, RMSE, and ACF and the residual analysis confirm the robustness of the ARIMA model and ensure the validity of the established conclusions. In addition, provided a solid foundation for monitoring the water quality of the Ghrib dam and allowed for the development of appropriate management plans aimed at protecting the ecological health of aquatic environments.

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