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Modelling and Forecasting of Dissolved Oxygen Using the ARIMA Model: The case of the Ledrat Dam (Medea Province-Algeria)

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SUMMARY:
Dissolved oxygen (DO) is a key indicator of water quality. This study focuses on the modelling of the temporal evolution of dissolved oxygen (DO) mg/L in the waters of the Ledrat dam, located in the wilaya of Medea, using the ARIMA model. The descriptive analysis shows significant variability in the dissolved oxygen values during the period of 2012-2022 with seasonal fluctuations and outliers greater than 12 mg/L, as well as the decomposed time series shows a nonlinear trend. The ARIMA model shows a good performance with an RMSE of 1.4191, an MAE of 1.0727 and a MAPE of 13.28%, which indicates adequate accuracy for the forecasts. The model validation using the L-Jung-Box test (Q=22.448, p-value=0.2625) confirms the independence of the residues, attesting to the quality of the fitted model. The results obtained prove that the ARIMA model is effective in capturing dissolved oxygen (DO) levels and providing relevant forecasts that can be used as a decision support tool to support the optimized management of the dam's water resources and preserve water quality.*
KEYWORDS: *dissolved oxygen, ARIMA model, L-Jung-Box test, Ledrat Dam.*

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; Messaoudi et *al.*, 2026)

Rapid urbanization, industrial expansion and intensification of agricultural practices have significantly increased the pollution of aquatic environments, both chronic and sporadic. Many rivers and reservoirs are now experiencing a continuous deterioration in their physico-chemical quality, under the effect of sustained anthropogenic pressure linked to domestic, industrial and agricultural discharges (Benoît and Comeau, 2005; Bekkoussa et *al.*, 2013; Abidi et *al.*, 2014; Benabdelmalek et *al.*, 2020).

Among the indicators of ecological health, dissolved oxygen (DO) is a fundamental parameter. It reflects the metabolic balance of aquatic ecosystems, resulting from the trade-off between photosynthetic production and the respiratory demand of biomass (Wetzel, 2001; Boyd, 2020). Maintaining sufficient oxygen levels is essential for the respiration of most organisms (fish, macroinvertebrates, and aerobic bacteria).

When DO concentrations fall below the critical threshold of 2mg/L, the waters are classified as hypoxic or even anoxic. This phenomenon represents a severe threat to biodiversity and leads to a profound alteration of biogeochemical cycles. The absence of oxygen promotes the release of nutrients and toxic compounds such as H_2S, $Fe2^+$, and $Mn2^+$ from sediments (Wetzel, 2001; Rabalais et *al.*, 2010; Jane et *al.*, 2021; Li et *al.*, 2023). These processes aggravate internal eutrophication and drastically reduce the biological richness of the environment (Nürnberg, 2002; Beutel, 2003; Søndergaard et *al.*, 2017).

Episodes of hypoxia are particularly common in deep dams. During the summer, thermal stratification isolates the deep layers (hypolimnion), preventing their reoxygenation and promoting an increased benthic consumption of available oxygen (Kraemer et al., 2021; Zhang et al., 2022). This phenomenon drastically limits the oxygen renewal of bottom water (Amieva et *al.*, 2023). Faced with the complexity of DO fluctuations influenced by nycthemeral cycles, terrigenous organic inputs and climate changes that accelerate deoxygenation (Kraemer et *al.*, 2021).

Modelling appears to be a crucial decision-making tool. The application of statistical time-series models, such as the AutoRegressive Integrated Moving Average (ARIMA) models, offers significant potential for predicting

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changes in water quality. These tools support ecological management in accordance with the requirements of the Water Framework Directive, which recommends thresholds of 5-6 mg/L to ensure good environmental status (European Commission, 2018). In this perspective, the present work aims to analyze a time series of dissolved oxygen over a period of 10 years at the Ledrat dam.
This study aims to analyze the time series of dissolved oxygen in order to understand its dynamics, and to identify seasonal variations and then to develop an ARIMA model allowing the modeling and forecasting of this essential parameter of water quality.

MATERIALS AND METHODS:

Study site

The Ledrat dam is located in the commune of Omaria, wilaya of Medea (**fig.01**), in the north of Algeria (35°58'N; 2°48'E). Commissioned in 1987, it is one of the major hydraulic structures in the catchment area of the Chiffa wadi, a tributary of the Medjerda river basin. With an initial storage capacity estimated at 85 million m*, this structure plays a strategic role in the supply of water for irrigation, local industry and human consumption in several municipalities in the wilaya of Médéa (ANRH, 2020; Benabdelmalek *et al.*, 2020).

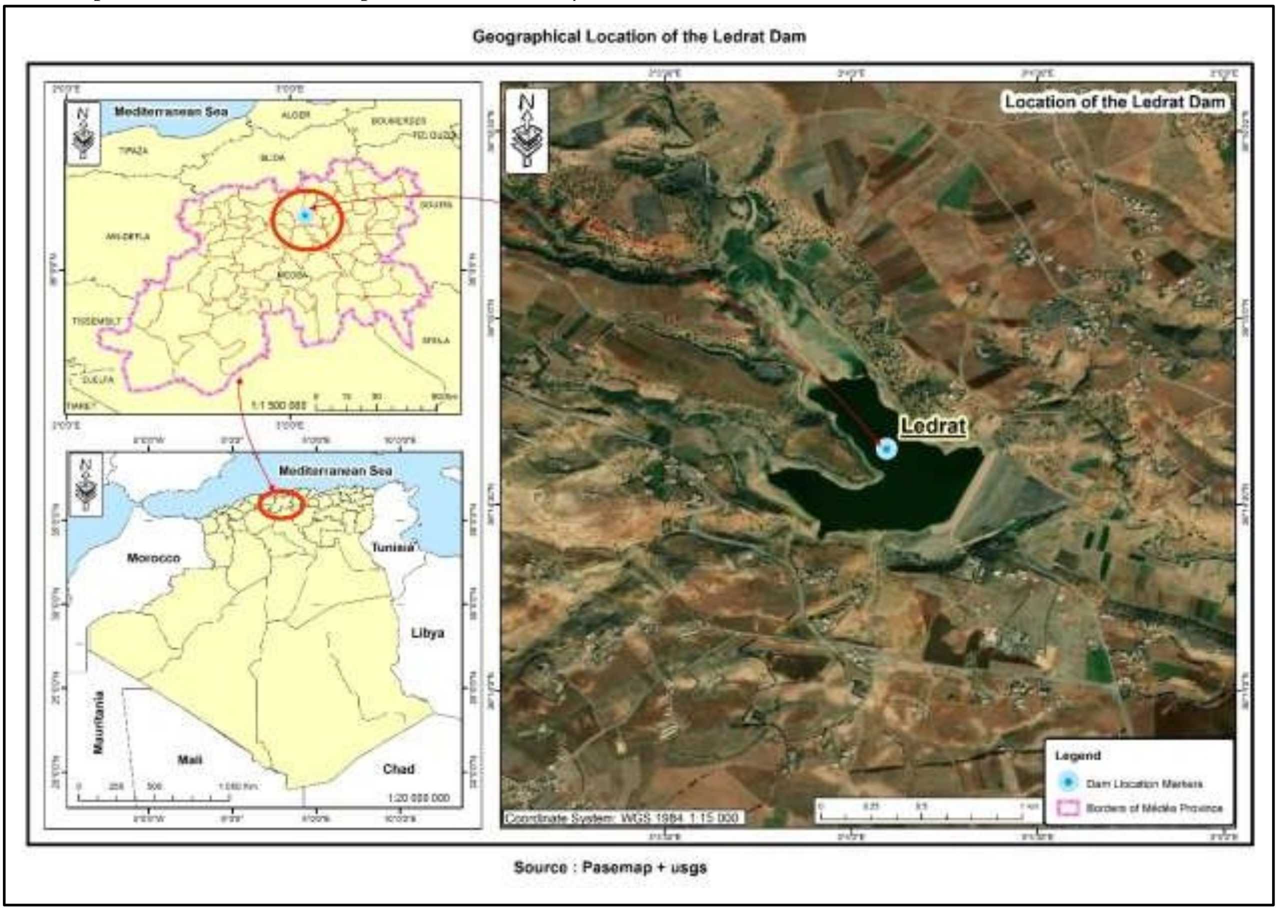

Figure 01: Map of the geographical location of the Ledrat Dam

Sampling Method:

Monthly measurements of dissolved oxygen (DO) are collected over a period of 10 years by the National Agency for Water Resources (ANRH, Station de Médéa.)
Water samples were collected monthly over a 10-year period (2012–2022)

Analytical methods:

Measurements of physicochemical parameters were performed *in situ* according to the standardized protocols of the APHA (American Public Health Association, 2017) and Rodier *et al.* (2021). Dissolved oxygen measurements were performed *in situ using a* portable HACH HQD DR-1900 **multiparameter probe** equipped with an optical LDO (Luminescent Dissolved Oxygen) probe. This optical sensor has the advantage of high accuracy (± 0.1 mg/L or ± 1% of the measured value), low drift and no oxygen consumption during measurement, unlike conventional electrochemical probes (HACH, 2020; Rode et al., 2016; Li et al., 2023; Boyd, 2020).

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Statistical analysis
The data obtained were statistically processed to identify trends and monthly variations in the physicochemical parameters of dissolved oxygen (DO). The data analysis was carried out using the R software (CRAN, 2024).

RESULTS AND DISCUSSIONS
The results of the analysis of the behaviour of the dissolved oxygen through two complementary approaches (fig.02), show that the dissolved oxygen values are generally centered around 8mg/L, with moderate variability and some outlier values above 12 mg/L.
The decomposition of the time series by the STL method highlights a general upward trend until 2018, followed by a marked and continuous decline between 2019 and 2022. This trend reversal suggests a recent deterioration in the dam's water quality, potentially related to increased organic loading, accelerated sedimentation, or the effects of climate change on water stratification and temperature (Søndergaard *et al.*, 2017; Zhang *et al.*, 2022; Li *et al.*, 2023; *Jane et al., 2021* ; *Kraemer et al., 2021*).

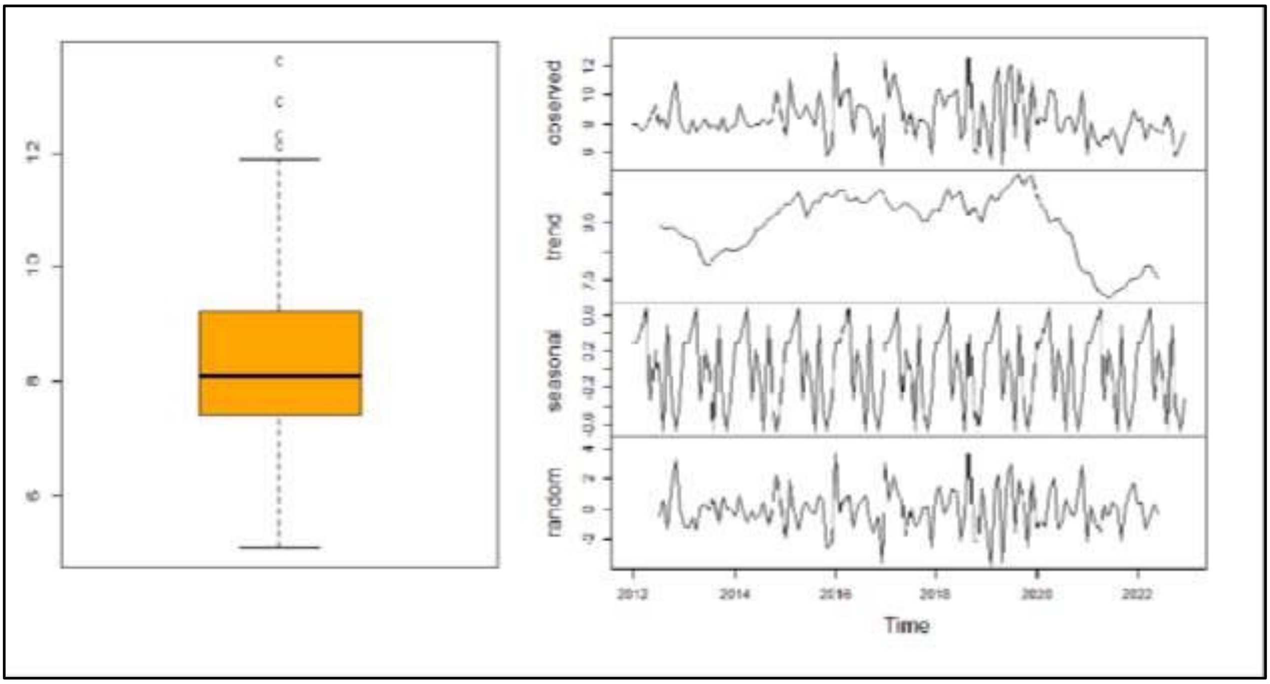

Figure 02: Descriptive analysis and decomposition of the oxygen time series below

The seasonal component is particularly pronounced, confirming the dominant influence of annual cycles on dissolved oxygen dynamics. The highest concentrations are generally observed in winter and spring, while minima are recorded in late summer and autumn, a period of thermal stratification and high bacterial decomposition activity (Wetzel, 2001; Nürnberg, 2002; Jane et al., 2021; Box et al., *1994* ; Yue et *al., 2002*; Messaoudi et *al., 2026*).
Finally, the analysis of decomposition residues shows relatively low and random values, indicating that the majority of the observed variations in DO concentrations are explained by the interannual trend and the seasonal cycle (Rabalais et al., 2010 ; Søndergaard et al., 2017 ; Li et al., 2023). These results highlight the need for enhanced monitoring of the recent decline in dissolved oxygen, as prolonged hypoxia could lead to serious ecological consequences, such as fish mortality, reduced aquatic biodiversity, and leaching of nutrients and heavy metals from sediments (Rabalais *et al.*, 2010 ; Søndergaard *et al.*, 2017; Kraemer *et al.*, 2021).

ARIMA MODEL RESULTS:
Verification of the Stationarity of the Data:
Before applying the ARIMA model, it is imperative to verify the stationarity of the time series, which is a fundamental condition for ensuring the statistical validity and predictive reliability of such models (Box *et al.*, 2015; Hyndman and Athanasopoulos, 2018; Box et al., 1994; *Shumway & Stoffer, 2017*). Indeed, nonstationarity can lead to biased estimates, unreliable forecasts, and misinterpretation of temporal relationships (Shumway and Stoffer, 2017; *Hyndman & Athanasopoulos, 2018*).
For this purpose, the augmented Dickey-Fuller test (ADF) was used. This test, widely used in hydrology and limnology for the analysis of water quality time series (Hirsch & Slack, 1984; Yue et *al.*, 2002; Zhang et *al.*,

2022), allows to test the null hypothesis (H_0) according to which the series has a unit root (non-stationary process) against the alternative hypothesis (H_1) of stationarity (Dickey and Fuller, 1979; Said and Dickey, 1984). The results obtained (p-value = 0.022 < 0.05) lead to the rejection of the null hypothesis at the 5% significance level. This statistic leads to the conclusion that the dissolved oxygen time series is stationary (at least in mean and variance). This statistical property ensures that the parameters of the ARIMA model (orders *p*, *d*, *q*) can be estimated robustly and that these coefficients will remain stable over time, a guarantee of reliability for short-term forecasts (Box et al., 1994; Parviz et al., 2010; Enders, 2015; Cryer and Chan 2008).

Model Results:

One of the most important and widely used time series models is the Box-Jenkins modeling approach, commonly referred to as the Autoregressive Integrated Moving Average (ARIMA) (Box et *al*., 1994).

ARIMA models are flexible in that they can represent several different time series, that is to say, pure auto-regressive (AR), pure moving average (MA), and combination AR and MA (ARMA) series, although they are limited by their assumed linear form (Parviz et *al*., 2010).

Table 01 : ARIMA model results

Metric	Value
Sigma^2	2.11
AIC	480.14
AICc	480.81
BIC	497.39
ME	-0.0516
RMSE	1.4191
MFA	1.0727
MPE (%)	-3.3944
MAPE (%)	13.2822
MASE	0.7073
ACF1	-0.0082

Note: **Sigma^2**: residual variance; **AIC**: akaike imformation criterion; **AICc**: Corrected Akaike Information Criterion; **BIC**: Bayesian imformation criterion; **ME:** mean error; **RMSE:** root mean squared error; **MAE:**mean absolute error; **MPE:** mean percentage error; **MAPE:** mean absolute percentage error; **MASE:** mean absolute scaled error; **ACF1**: autocorrelation function at lag 1

Analysis of the results obtained for the ARIMA model (3,1,1) (1,0,0), applied to dissolved oxygen (DO) data, indicates a robust and well-fitting model. Fit metrics, such as AIC (480.14), AICc (480.81), and BIC (497.39), show reasonably low values, indicating that the model achieves a good trade-off between complexity and accuracy. The prediction errors (MOE = -0.0516, RMSE = 1.4191, MAE = 1.0727) are small, which reinforces the idea that the model effectively captures the variations of the series. The p-value of 0.2625 from the Ljung-Box test confirms that the model residuals do not have significant autocorrelation, which is essential for a well-fitting ARIMA model.

Residue Analysis and Model Validation:

The validation of the ARIMA model (3,1,1) (1,0,0) [12] was carried out through several statistical and graphical diagnoses in order to verify the quality of the fit and the absence of significant residual structure.

Table 02 : Model Validation

Metric	Value
Q*	22.448
Degrees of Freedom (df)	19.0
P-value	0.2625
Model Degrees of Freedom	5.0
Total Delays Used	24.0

The Ljung-Box test was applied to the model residues. The results **(Tab. 2)** show a Q* value of 22.448 for 19 degrees of freedom, associated with a p-value of 0.2625. Since this value is above the significance level of 0.05, the null hypothesis of the absence of significant autocorrelation of the residues cannot be rejected (Ljung and Box, 1978; Box et *al.*, 2015; Hyndman & Athanasopoulos, 2018). This result indicates that the residues behave like white noise, an essential condition for validating an ARIMA model (Hyndman and Athanasopoulos, 2018; Shumway and Stoffer 2017).

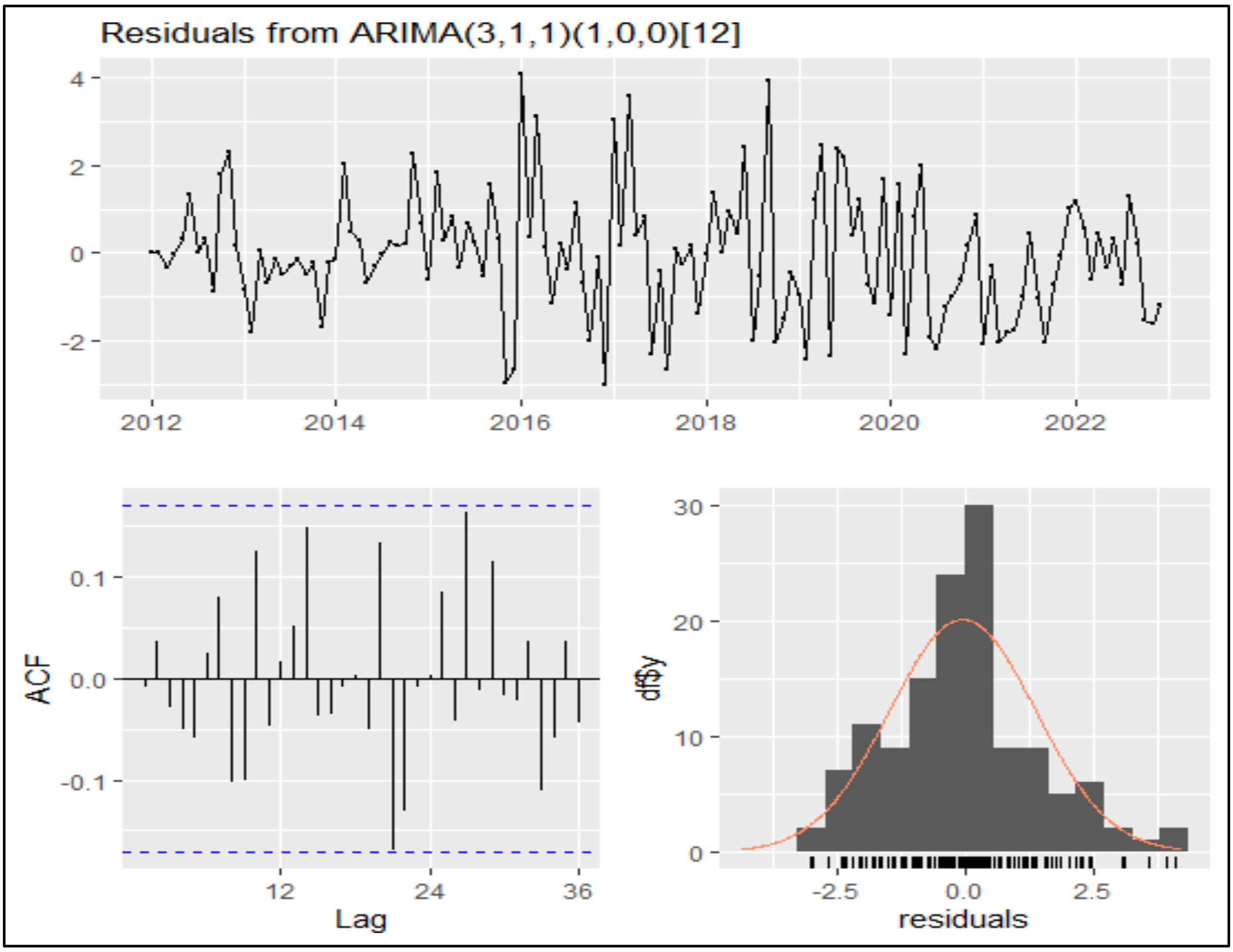

Figure 03: Analysis of model residuals

Graphical examination of the residues (Figure 4) shows random fluctuations around zero with no systematic trend or residual cyclic structure, in accordance with the visual validation criteria recommended for environmental time series (Hirsch & Slack, 1984; Yue et *al.*, *2002*; Cryer and Chan, *2008*). The analysis of the autocorrelation function (ACF) of the residuals confirms that all autocorrelation coefficients remain included in the 95% confidence intervals, showing the absence of significant serial correlation (Brockwell & Davis, 2016). On the other hand, the examination of the distribution of the residues (histogram and Quantile-Quantile diagram) indicates a reasonable approximation to a normal distribution, although slight asymmetries are observable. This near-normality of the residuals is important because it ensures the validity of the confidence intervals and statistical tests associated with the model (Shumway and Stoffer, 2017; Brockwell and Davis, 2016).

In summary, all the statistical and graphical diagnoses confirm that the ARIMA model (3,1,1)(1,0,0) is adequate for modelling and predicting dissolved oxygen levels in the Ledrat dam, particularly in the context of dissolved oxygen monitoring and anticipation of hypoxia risks (Amieva et *al.*, 2023; Zhang et *al.*, 2022).

Forecasts:

Figure (04) illustrates the predictions of the dissolved oxygen values by the ARIMA model.

It can be seen that the observed values show significant variability over the period studied, while the forecasts indicate a relatively stable evolution around 7-8 mg/L.

The forecast intervals indicate that there is significant uncertainty, related to the natural variability of dissolved oxygen and the fluctuations observed in the time series.

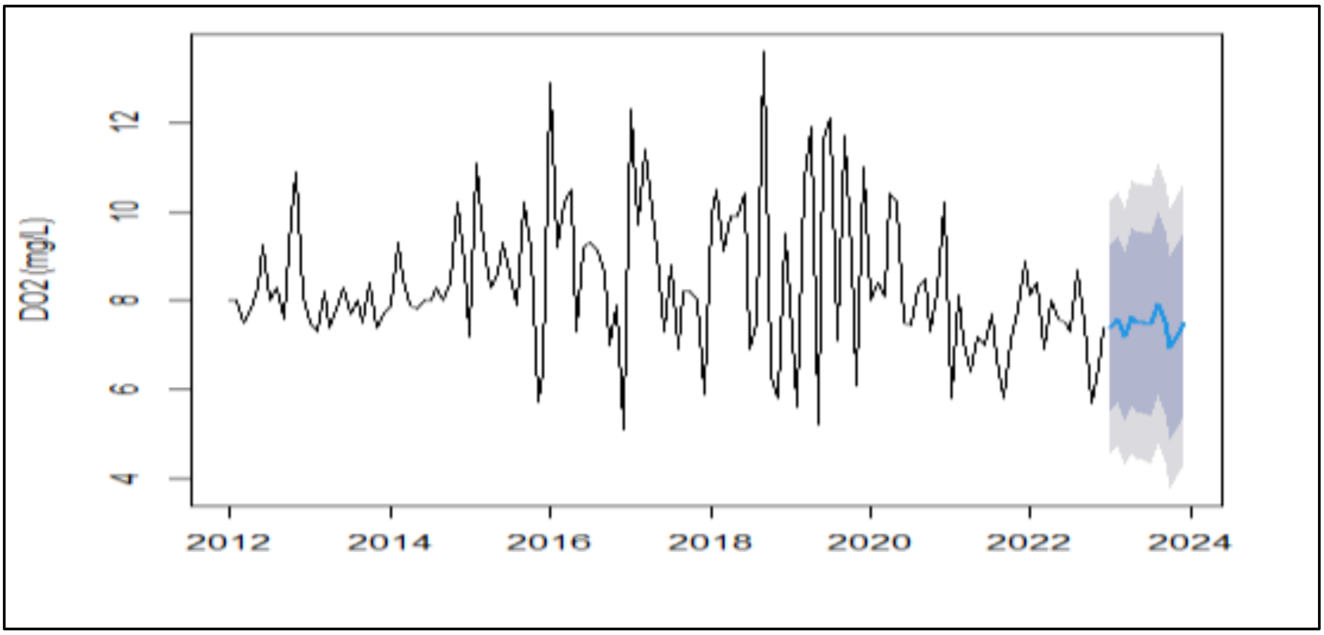

Figure 04: Predictions of dissolved oxygen values (DO2)

CONCLUSION:

In conclusion, the ARIMA model (3,1,1) (1,0,0) [12] has proven to be adequate and robust for modelling and predicting the spatio-temporal variations of dissolved oxygen (DO) in the waters of the Ledrat dam over the period 2012–2022. The fit criteria (AIC, AICc, BIC), the residue analysis, the Ljung-Box test ($p = 0.2625$) as well as the examination of the autocorrelation functions confirm that the model effectively captures the temporal structure of the series, both in its trend and seasonal components, without significant residual autocorrelation or systematic bias.

The good performance of the model, illustrated by moderate prediction errors (RMSE = 1.42 mg/L; MAE = 1.07 mg/L; MAPE = 13.28%), demonstrates its reliability in making short- and medium-term forecasts. These forecasts are a valuable operational tool for managers, allowing them to anticipate hypoxia episodes, identify critical periods and implement appropriate preventive measures.

However, the marked decline in dissolved oxygen observed between 2019 and 2022 raises concerns about the gradual deterioration of the dam's water quality. This phenomenon, likely amplified by climate change, thermal stratification and anthropogenic inputs, could lead to important ecological consequences, such as fish mortality, nutrient release from sediments and the development of cyanobacteria.

Ultimately, this work demonstrates the interest of ARIMA modelling approaches combined with long time series analysis for the monitoring and sustainable management of reservoirs. It paves the way for the integration of these models with remote sensing and machine learning approaches, to improve the prediction and proactive management of water quality in Algerian dams.

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