Statistical forecasting of water temperatures and dissolved oxygen concentrations for monitoring water quality in reservoirs: A SARIMA modeling-based application

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Abstract

Water temperatures (T) and dissolved oxygen concentrations (DO) have a great deal of significance for monitoring water quality is surface waters such as reservoirs since the interaction between them maintains the ecological balance Hence, applying the advanced monitoring models that require continuous field measurements of high cost and accuracy is complicated, especially for the developing countries where data is insufficient. In this paper, a statistical-based model, the seasonal autoregressive integrated moving average model (SARIMA), was employed for forecasting water temperatures and dissolved oxygen concentrations in Saddat Al-Hindiyah Reservoir, Iraq, using monthly measurements during a study period of four years (2021-2024). Results indicated to a seasonal period length of 12 months and identified two models [SARIMA(5,0,1)(1,0,0)12 and SARIMA(0,1,2)(0,1,1)12] for forecasting an entire year period of water temperatures and dissolved oxygen time series, respectively, after training the models during the years (2021-2023) and testing them during the year 2024. Consequently, the SARIMA model captured the temporal patterns in field data with good agreement. The model exhibited a satisfactory performance for water temperatures by achieving Mean Absolute Errors (MAEs) of 2.384 °C and 3.813 °C for the training and testing phase, respectively, while for dissolved oxygen MAEs were 1.026 mg/L and 0.445 mg/L for both phases, respectively. According to that an inverse relationship between the reservoir's water temperatures and dissolved oxygen concentrations revealed strongly. Furthermore, the models' forecasting results highlighted the reservoir water temperatures range of (18.073-27.790) °C with a mean value of 23.562 °C, and the reservoir dissolved oxygen concentrations range of (5.078-7.643) mg/L with a mean value of 6.271 mg/L above the minimum permissible limit. Thus, the study suggest that SARIMA model can be a useful tool for monitoring water quality in surface waters due to it applicability in capturing temporal patterns, trend, and seasonality in time series data with low computational cost using single univariate time series.

Keywords: Dissolved oxygen, reservoirs, SARIMA, statistical forecasting, time series forecasting, time series analysis, water temperature, water quality monitoring

1. Introduction

Monitoring and forecasting water quality, mainly dissolved oxygen concentrations and water temperatures, are essential for reservoirs development and management (Lehner et al., 2011; Tavera-Quiroz et al., 2023; Ma et al., 2025), maintaining biodiversity and preserving healthy aquatic ecosystems (Venkatraman et al., 2025). However, the continuous industrialization, urbanization, and increased human activities have their shared effect on the

aquatic ecosystem and water quality (Vörösmarty et al., 2010; Xia et al., 2024). The level of dissolved oxygen acts as an important indicator in ensuring water safety for human consumption and maintaining aquatic lives (Bačová Mitková et al., 2024). The low dissolved oxygen levels increase Biochemical Oxygen Demand (BOD) as a result of organic matter and algae decay, especially during high temperature seasons. Hence, when the dissolved oxygen levels become below the minimum permissible limit, typically 4.0 mg/L (DEQ, 1995), the reservoir water's health and aesthetics are impacted negatively due to the related high respiration rates and decomposition processes (Xie et al., 2023), causing odor problems and killing fish (Maruthai et al., 2025). Water temperature is a key water quality parameter that forces the reservoir dissolved oxygen levels inversely since temperature regulates the metabolic activity of aquatic organisms in addition to its influence on the oxygen reaeration process (Yavuz, 2025). By knowing the seasonal variation of both dissolved oxygen and water temperature, the interaction between them can also be addressed. Accordingly, the dissolved oxygen and water temperature variation can shift the aquatic ecosystem biodiversity state significantly (Bačová Mitková et al., 2024). Therefore, the future forecasting of dissolved oxygen and water temperature is crucial for the sustainable management of reservoir systems.

The rapid growth in computer technology can enhance the water quality management, which leads to develop water quality models with a varied range of complexity. Numerous water quality models with different requirements are commonly used, which have their advantages and restrictions (Ziemińska-Stolarska & Skrzypski, 2012; Olowe & Vellaisamy Kumarasamy, 2018). Hence, the modeling of water quality in reservoirs remains a challenging task because of its limitations to field data availability and required model complexity. Among these models, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is considered one of the most classical statistical approaches for forecasting time series data and its components, offering strong capability in identifying temporal structure of trend, seasonality, cycles, and noise (Chango et al., 2025). Due to the SARIMA model robust temporal features extraction ability, the SARIMA model has been widely utilized in a varied range of time series analysis and forecasting studies (Tadesse & Dinka, 2022; Ahmadpour et al., 2023; Long et al., 2023; Chango et al., 2025). One of the main advantages of using the SARIMA model is that it can be built based on a univariate time series of any water quality parameter. This will be useful in case of limited data set (Myllis et al., 2024). Thus, data-driven time series analysis with SARIMA modeling-based forecast would be valuable for evaluating dissolved oxygen and water temperature in surface waters without complex in-situ requirements such as water hydrodynamics.

The time series forecasting using the SARIMA model has been applied in literature for surface water with various ways depending mostly on the water quality target parameter, time series data availability, modeling framework, and accuracy metrics. Islam et al. (2024) applied the SARIMA model to evaluate the monthly water quality data in the two main basins of the Yangtze and Yellow River, China, from 2004 to 2018. Three univariate time series of water quality parameters (dissolved oxygen, permanganate, and ammonium nitrogen) were used to determine the Comprehensive Water Quality Identification Index (CWQII) time series to be forecasted alongside with dissolved oxygen time series. Depending on the autocorrelation function (ACF), partial autocorrelation function (PACF), the SARIMA model parameters were chosen. This application employed the Akaike's Information Criterion (AIC) to select the best combination of SARIMA parameters for the final model, and used the Mean Absolute Percentage Error (MAPE) metric to measure the model accuracy. The main finding highlighted that the SARIMA model was the supreme suitable tool for predicting the upcoming values of CWQII and dissolved oxygen with MAPEs of (CWQII: 0.091 and 0.089) for the Yangtze River basin and (CWQII: 0.133 and 0.0987) for

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the Yellow River basin, recommending the final model as a water control approach. A similar application was performed by Soetan et al. (2024). They used SARIMA model to forecast the water quality index (WQI) time series in an Urban River (New Jersey, U.S.) from 2004 to 2019, employing the rolling window cross-validating for the model training to improve the long term predictions (2014 to 2019). Hence, the WQI was calculated based on many water quality parameters including water temperature and dissolved oxygen. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), MAPE, and Theil inequality were the metrics of model performance. Accordingly, a minimum MAPE value of 0.229 was achieved by the model. Even though cross-validation was adopted in this model application, the MAPE was high compared to the previous application. Another study was performed by Bačová Mitková et al. (2024). Dissolved oxygen time series data from the Váh River basin, Slovakia, was used to develop the SARIMA model for the period from 1999 to 2021. The final model was selected based on the AIC, and the model performance was evaluated by the correlation score (R) and RMSE. Results showed that the dissolved oxygen accuracy ranged between 0.71 and 0.92 for the R metric and less than 1.46 mg/L for the RMSE metric. In addition, the corresponding water temperature was forecasted using the linear and nonlinear regressions between the time series of water temperature and dissolved oxygen, revealing an inverse relationship between the two water quality parameters. Hence, the monthly dissolved oxygen levels have maximum values during the winter season and minimum values during the summer season, and the monthly temperatures have maximum values during the summer season and minimum values during the winter season. Noticeably, the study reached to a conclusion that the SARIMA model is very efficient for modeling the monthly dissolved oxygen time series with seasonality. Kogekar et al. (2021) forecasted the univariate time series of dissolved oxygen and biological oxygen demand (BOD) in the Ganga River, Bengal, from the period 2016 to 2020 in order to have low cost implementation for monitoring and forecasting the river water quality parameters. Three models were developed including Autoregressive Integrated Moving Average (ARIMA), SARIMA, and Prophet. Both SARIMA model and Prophet model predicted the river water quality accurately, (DO MAEs: 0.66 mg/L and 0.55 mg/L, respectively) and (BOD MAEs: 0.765 mg/L and 0.714 mg/L, respectively).

Regarding the above statistical modeling applications of time series forecasting, it is useful to implement the SARIMA model for improving the environmental management controls. This is necessary to provide a solution for a certain water quality problem, especially for the underdeveloped and developing countries, since the SARIMA model is built based on a single time series. Hence, the required information to develop other models, such as theoretical and numerical water quality models, are not available in these countries completely. In Iraq, the Saddat Al-Hindiyah Reservoir, where the Hilla River headwater exists, hasn't been managed well related to water quality due to lack of continuous data availability. In this research, the SARIMA model was utilized to predict and forecast the temporal variation of water temperatures and dissolved oxygen levels in this reservoir based on monthly univariate time series data measured at the reservoir during the period from 2021 to 2024. The present modeling framework was processed uniquely by leveraging the model metrics between the training phase and the testing phase in order to capture the temporal patterns, trend, and seasonality of water quality parameters. Thus, developing such a model helps explore the impact of both water quality parameters on the reservoir ecosystem without collecting other interacting constituents and parameters.

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2. Materials and methods

2.1 Study area

One of the essential Iraqi water resources which deserves a great deal of study is Saddat Al-Hindiyah Reservoir (Figure 1). It is the headwater of the Hilla River and the lower part of the Euphrates River, which are the main sources for drinking water in the region. The reservoir is located to the Hilla City north direction in Babylon Governorate, longitude: 44°16′05.7" E / latitude: 32°43'55.5" N / elevation: 31.4 m above sea level. It is considered as one of the pioneering irrigation projects in Iraq and provides safe water for agricultural areas in the governorates, surrounding the Hilla River. Additionally, this reservoir endures fish and other aquatic lives that reside in the river. Therefore, the reservoir water quality is important to monitored. Two parameters of water quality affect the surface water ecosystem significantly, the water temperature and the dissolved oxygen level. They are closely related and have direct and indirect effects on the reservoir health (Al-Ridah, et al., 2021; Jane et al., 2021; Dadi et al., 2020; Al-Dalimy & Al-Zubaidi, 2023; Johnson et al., 2024; Al-Saadi & Al-Zubaidi, 2025; Ma et al., 2025).

The reservoir inflow, from the upper part of the Euphrates River carries substantial amounts of sediments and floating plants that are accumulated at the reservoir water body, degrading the aquatic ecological health. The case will be worse with high water temperatures. The high water temperature increases the growth of algal, chemical reaction and biological reaction rates of decomposition. Hence, this causes an oxygen depletion issue. A sufficient dissolved oxygen level allows the aerobic microorganisms to analyze organic matter efficiently. However, the low levels of dissolved oxygen causes anaerobic decomposition, producing ammonia, methane, and hydrogen sulfide, that leads to degrade water quality significantly (Tan et al., 2013; Maruya et al., 2023; Ji et al., 2023; Zhang et al., 2024). Typically, the dissolved oxygen level, required for the survival of aquatic life such as fish and other organisms must be more than 4.0 mg/L (DEQ, 1995; Rouf et al., 2022; Akratos et al., 2025).

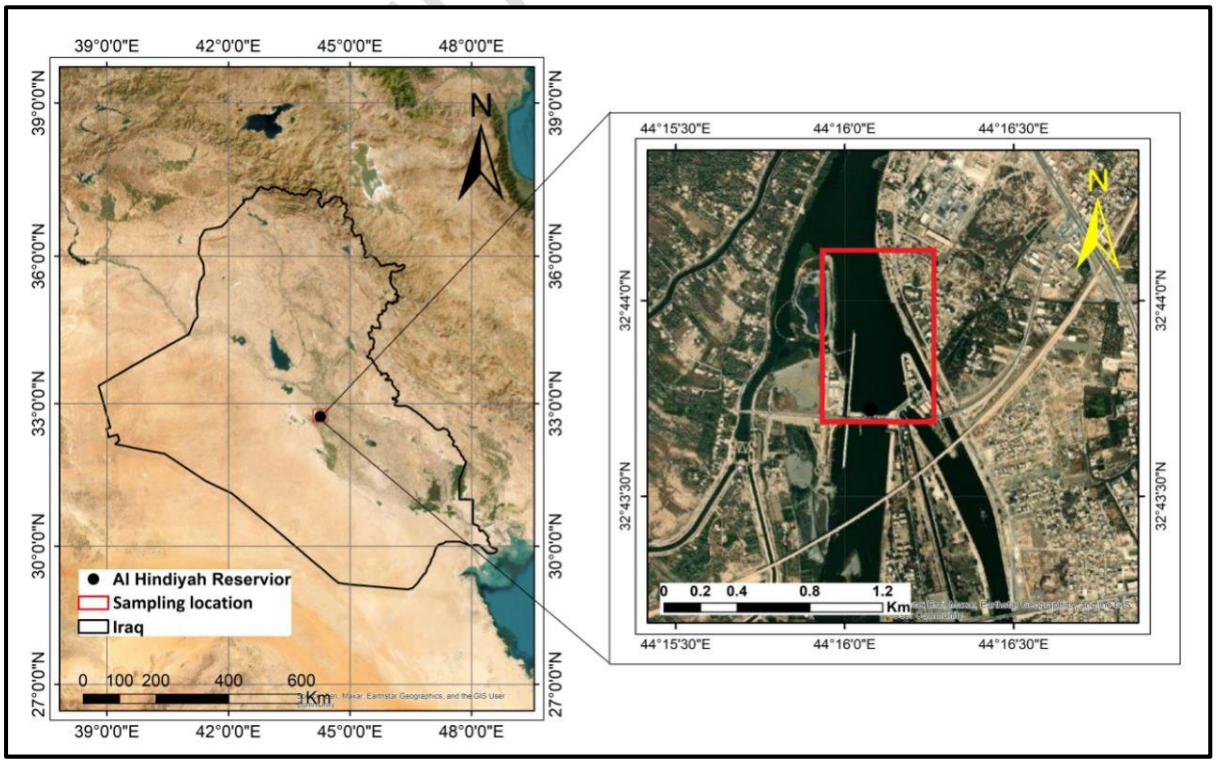


Figure 1. Study area and sampling location.

2.2 Sampling procedure and records

The sampling procedure involved taking water samples from the study area, the red rectangular area in Figure 1, and measuring the dissolved oxygen concentration (DO) and water temperature (T) by using the portable DO meter and thermometer, following the standard methods of water examination (APHA, 2017). The samples were taken in which the entire reservoir area was covered. Accordingly, the study area was divided into three stations: One station is close to the inflow site at the northern side, second station is in the middle, and third station is close to the outflow site (the barrage location) at the southern side. This sampling procedure were conducted every month over a 4-years period (2021-2024) by the Babylon Environment Directorate / Ministry of Environment / Iraq and the Department of Environmental Engineering / Faculty of Engineering / University of Babylon / Iraq. Every month, three samples were taken at each station, averaged, and recorded as a univariate time series for dissolved oxygen concentrations (DO) and water temperatures (T) as shown in Figure 2.

The average water temperatures vary slightly during the study years with an averages values of (23.6, 24.08, 23.82, and 23.75) °C during the years (2021, 2022, 2023, 2024, respectively). The highest value of temperature was 32.32 °C in 2024, and the lowest value was 12.12 °C in 2024 too. On the other hand, the average values of the dissolved oxygen concentration were (8.16, 7.68, 6.81, and 6.59) mg/L during the years (2021, 2022, 2023, and 2024, respectively). The highest value was 10.15 mg/L in 2022, and the lowest value was 5.27 mg/L in 2024. In addition, the average values of water temperatures and dissolved oxygen concentrations during the entire four years were 23.81°C and 7.31mg/L, respectively, which is acceptable compared to the minimum level limitation of dissolved oxygen (4.0 mg/L). Hence, the relationship between the two water quality parameters is inversely correlated with a Pearson correlation coefficient (r) of -0.55 [95% CI: (-0.72, -0.31)]

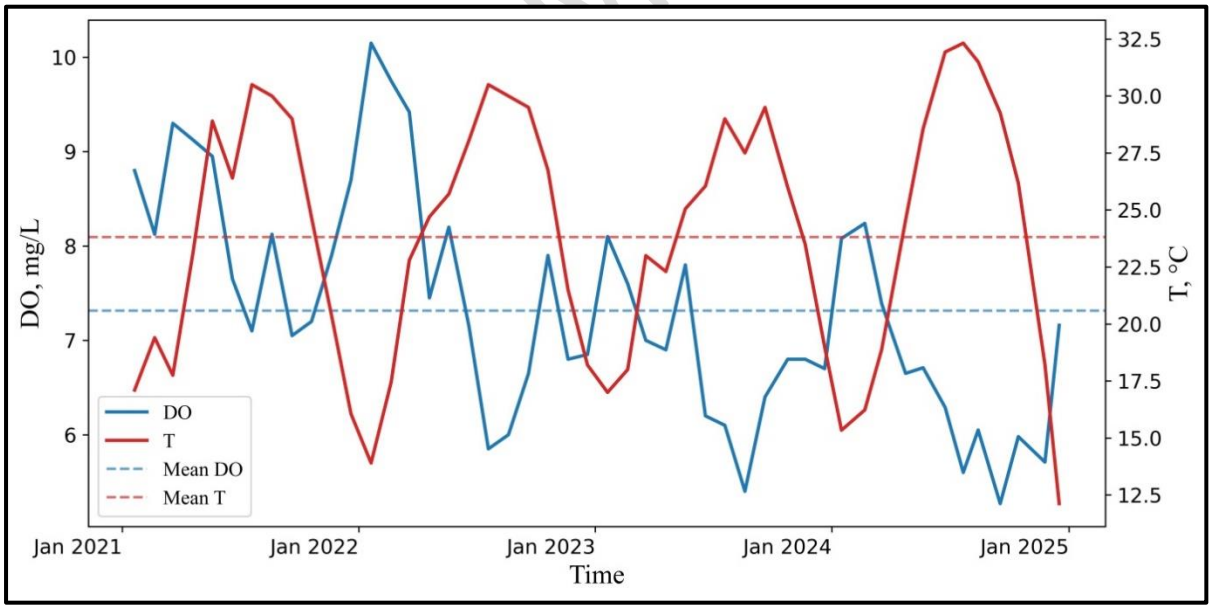


Figure 2. Annual variation of dissolved oxygen concentrations (DO) and water temperatures (T) in Saddat Al-Hindiyah Reservoir during the period (2021-2024).

2.3 SARIMA model

The extension of the Autoregressive Integrated Moving Average model (ARIMA) after adding the seasonality effect is the seasonal-ARIMA model, called SARIMA model. The model is built based on three components (Autoregressive (AR), Integrated differencing

(I), and Moving Average (MA)) to forecast the future values from the past values, incorporating both non-seasonal and seasonal effect of the time series. The SARIMA model can be represented as SARIMA(p,d,q)(P,D,Q)s and expressed as shown in Eq. 1 mathematically in which p, d, and q are the non-seasonal component orders of autoregressive, integrated differencing to remove the time series trend and make it stationary, and moving average, respectively, P, D, and Q are the seasonal component orders of autoregressive, integrated differencing to remove the time series seasonal pattern and make it stationary, and moving average, respectively, and s is the seasonal period length (Tadesse & Dinka, 2022; Myllis et al., 2024; Dahiya et al., 2024; Yulianti et al., 2025).

$$\{\Psi_P L^s\} \times \{\psi_p L\} \times \{(1-L^s)^D\} \times \{(1-L)^d\} \times w_t = \{\Phi_Q L^s\} \times \{\phi_q L\} \times \varepsilon_t \quad (1)$$

Where; w_t is the observed value of any water quality parameter (T or DO) at time t, ε_t is the white noise error (at time t, L is the backshift operator that allows to express all lags compactly in which $L^n y_t = y_{t-n}$, $\Psi_P L^s$ is the seasonal autoregressive component operator of order P, $\psi_p L$ is the non-seasonal autoregressive component operator of order p, $\Phi_Q L^s$ is the seasonal moving average component operator of order Q, $\phi_q L$ is the non-seasonal moving average component operator of order q, and $(1-L^s)^D$ and $(1-L)^d$ are operators account for seasonal and non-seasonal differencing component of order D and d, respectively. Thus, zeroing the D or d value turns off the seasonal or non-seasonal differencing in the model, respectively.

It is important to notice that the SARIMA model required the time series to be stationary. Practically this means the time series needs to be transformed by taking differences to remove the seasonal patterns or systematic trends. The SARIMA model is inherently considered as a linear model which assumes the relationship between the current value of the time series and the past value is linear. Additionally, the model residuals must be white noise and normally distributed (Masena & Shongwe, 2024; Yang et al., 2025; Ibanez et al., 2024).

2.4 Study framework

The SARIMA model was implemented within the python environment (Python Softwere Foundation, 2016) as displayed in Algorithm I, which is the pseudocode of model development process, and Figure 3, which is the general framework of the study. After collecting the field data measurements of temperature and dissolved oxygen time series, both series were evaluated for stationarity and seasonality. The time series visual inspection mention to a strong seasonal pattern (Figure 2). This can be clearly noticed by decomposing both time series into their components as shown in Figures 4 and 5. Noticeably, the dissolved oxygen time series shows non-stationery behavior due its additive seasonal pattern around the downward trend. The periodic correlation pattern can be confirmed by plotting the ACF and PACF correlograms (Tadesse & Dinka, 2022; Mphanya et al., 2025) as depicted in Figures 6 and 7. Hence, the seasonal period is repeated every 12 months (s=12).

The Augmented Dickey-Fuller (ADF) test was utilized to assess the time series stationarity computationally (Iswari et al., 2022; Kwarteng & Andreevich, 2024; Mphanya et al., 2025). Hence, the test null hypothesis, which is the time series is non-stationary, was rejected for temperature (ADF statistic=-5.540308 and p-value=0.000002) and accepted for dissolved oxygen (ADF statistic=-0.626535 and p-value=0.864873) using a p-value of 0.05 threshold (K, L. et al., 2025). Accordingly, the temperature time series is stationery, and the dissolved oxygen time series is not. Therefore, the dissolved oxygen time series needs to be transformed to make it stationary. It was found that non-seasonal and seasonal single integration were needed to make the dissolved oxygen time series stationary (d=1 and D=1).

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The first difference was taken by subtracting the previous value from each value in the time series. This degree of differentiation made the dissolved oxygen time series stationary (ADF statistic=-5.104509 and p-value=0.000014), following the ADF test alternative hypothesis of stationary time series.

Because the spikes in ACF and PACF plots tail off toward zero unclearly, the other non-seasonal and seasonal component orders of the SARIMA model, (*p* and *q*) and (*P* and *Q*), respectively, were obtained by training the SARIMA model using "auto_arima" function from "pmdarima" library (Smith et al., 2017). Hence, the function builds many SARIMA models of different combinations of orders. The model of minimum Akaike's Information Criterion (AIC) value is the final model to be diagnosed as shown in Table 1 and 2. The AIC metric is considered as a tool for the model selection to make good predictions and prevent the overfitting in train data (Farsi et al., 2021; Masena & Shongwe, 2024; Dinamarca et al., 2025). Furthermore, the Jarque-Bera (L1) (JB) and Ljung-Box (Q) tests were utilized to diagnose whether the selected model fitted the train data well. Thus, the final model residuals need to be normally distributed (Prop (JB) > 0.05) and uncorrelated (Prop (Q) > 0.05).

Moreover, after identifying the two final SARIMA models (the first one is for the water temperatures forecasting and the second one is the dissolved oxygen forecasting), they were tested to forecast the test data. Finally, assessing the performance of the developed SARIMA model usually includes the use of statistical metrics. In this study, the model performance was evaluated by the Mean Absolute Error metric (MAE) as depicted in Eq. 2, which is the absolute average magnitude of difference between the observed values (Y_i) and predicted values (M_i) based on a number of observations (n), to measure the model accuracy. The MAE gives the error with the exact same unit as the data that SARIMA model is trying to forecast, providing a reliable baseline to compare different models. Hence, it is robust regarding both data outliers and values sign. The lower MAE in magnitude, the best predictive accuracy (A. M. Al-Zubaidi & Wells, 2018; Kwarteng & Andreevich, 2024; Granata et al., 2024).

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \sum |Y_i - M_i|}{n} \tag{2}$$

Algorithm I: The SARIMA model development steps:

- **Start**
  - ***Reading*** *the dataset of water temperatures and dissolved oxygen*
  - ***Exploring*** *and* ***cleaning*** *the dataset and* ***creating*** *monthly univariate time series for each parameter*
  - ***Applying stationarity tests:*** *Dickey–Fuller test and ACF and PACF Plots.*
  - ***Checking stationary:*** *If dataset is not stationary, take differences*
  - ***Setting*** *the seasonal and non-seasonal component orders of SARIMA model (p, d, q, P, D, Q, s)*
  - ***Splitting*** *the entire dataset into Train and Test dataset*
  - ***Evaluating*** *the model by* ***calculating*** *and* ***checking*** *AIC, model residuals, and MAEs simultaneously*
  - ***Making*** *predictions depending on the final model*
- **End**

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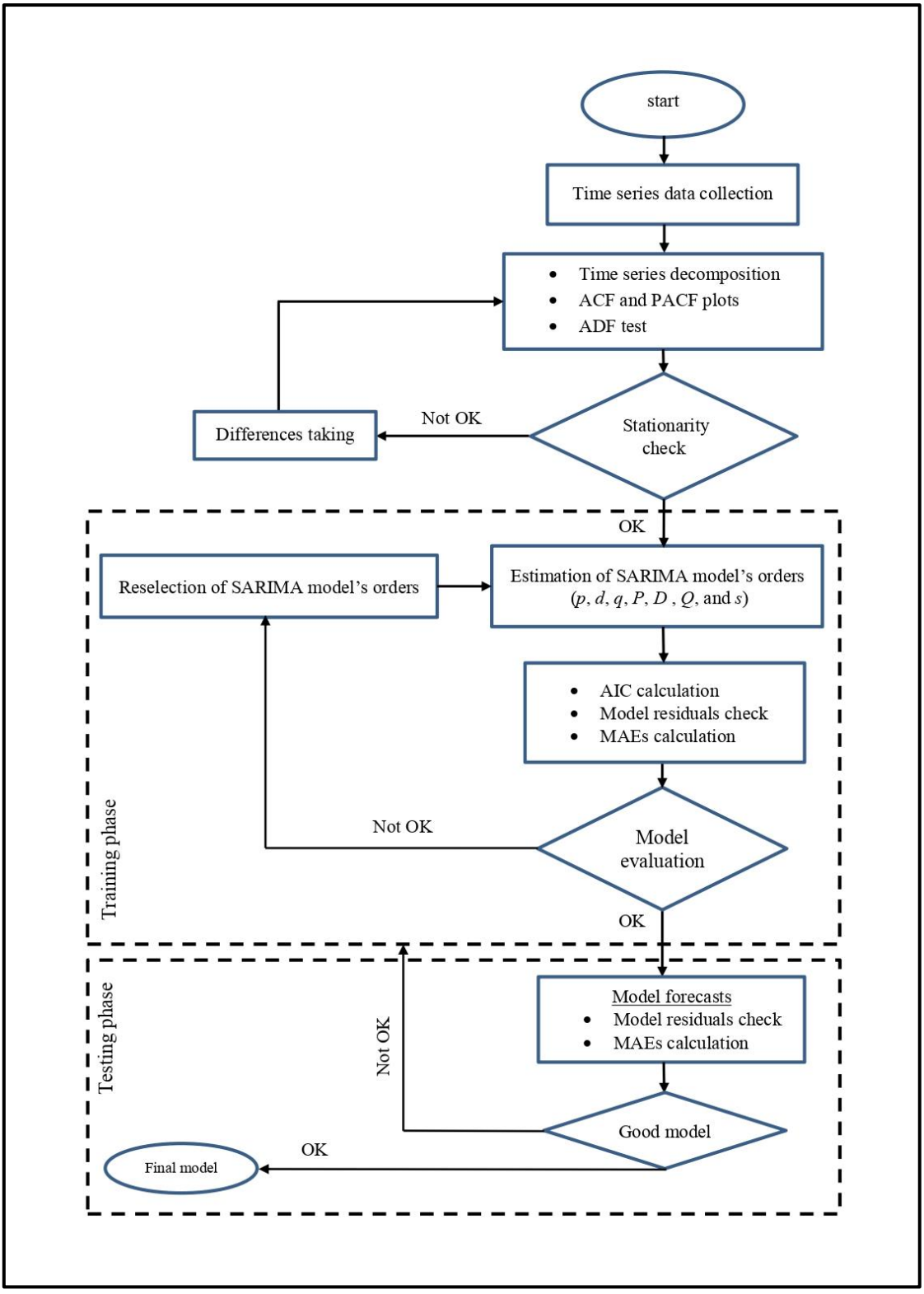


Figure 3. The SARIMA model implementation framework.

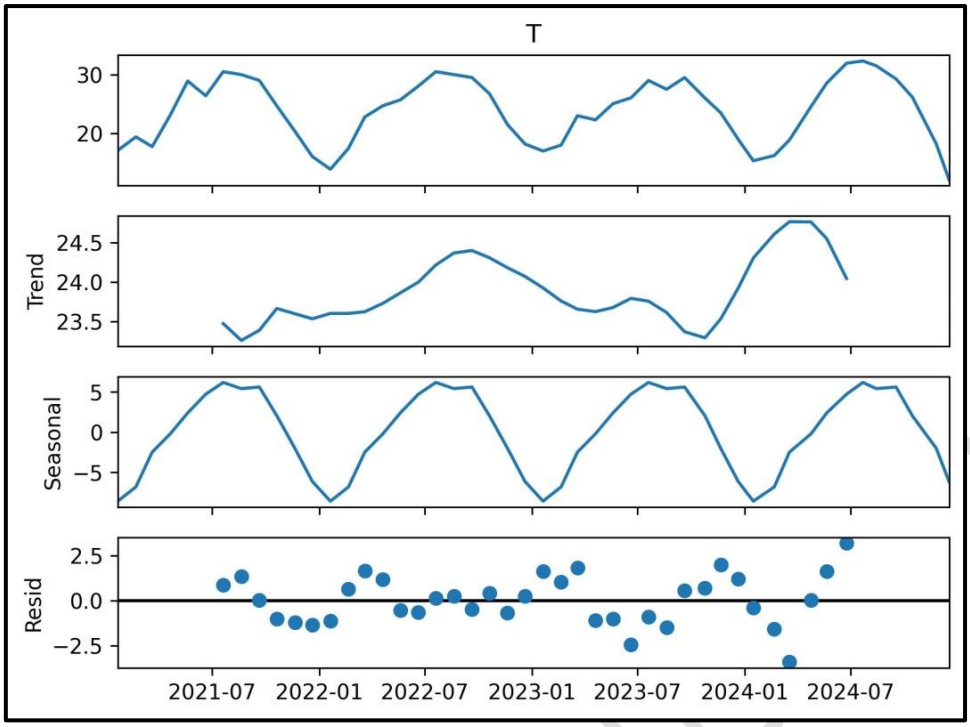


Figure 4. Water temperatures time series pattern decomposition.

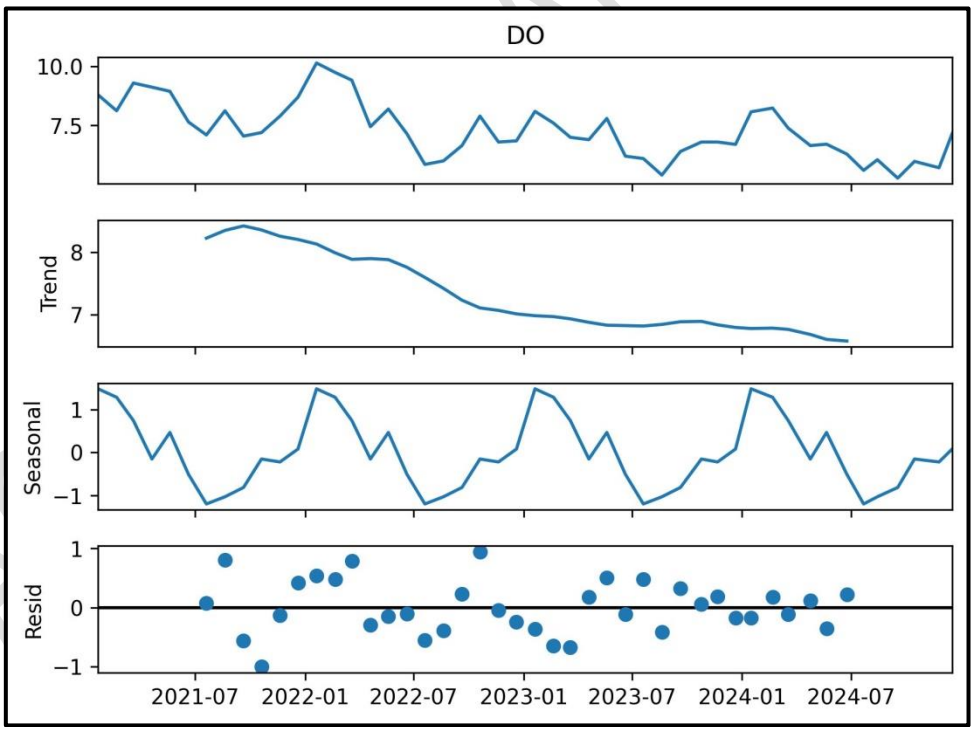


Figure 5. Dissolved oxygen time series pattern decomposition.

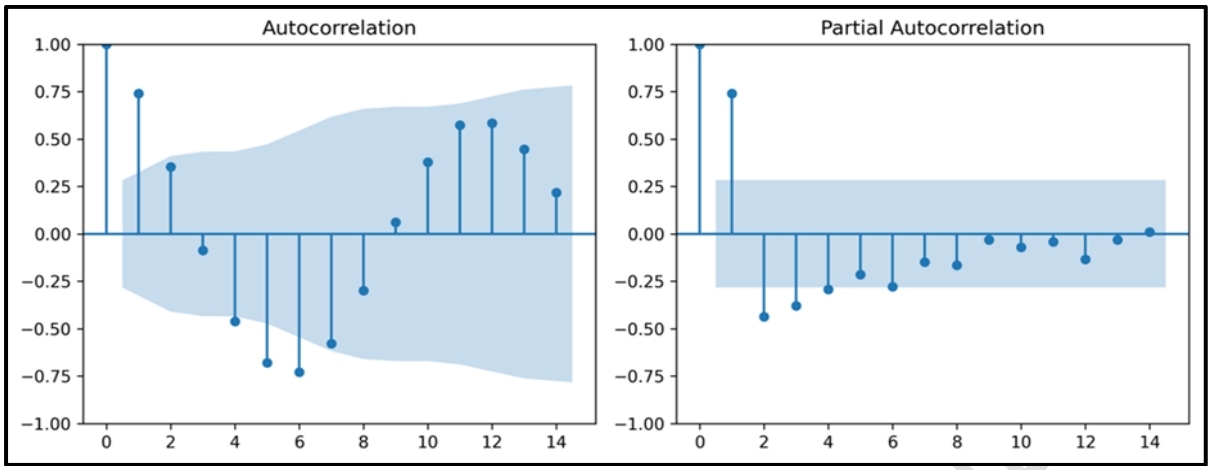


Figure 6. ACF and PACF plots of the water temperatures times series

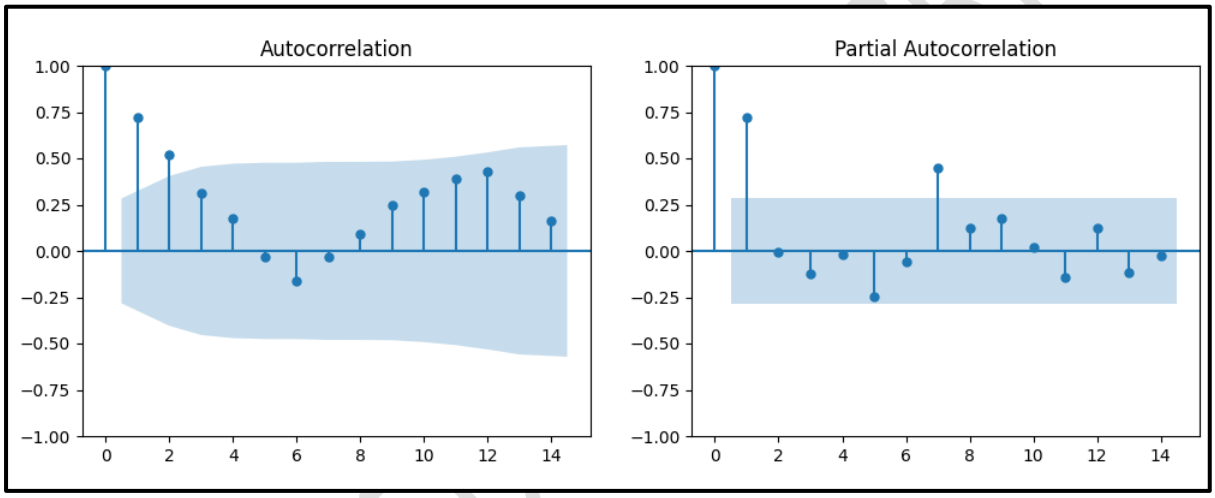


Figure 7. ACF and PACF plots of the dissolved oxygen times series.

Table 1. The best combinations of orders for the SARIMA model to fit and forecast the water temperature time series.

Orders combinations (p, q, P, Q)	**AICs**	**Jarque-Bera (L1) Prop (JB)**	**Ljung-Box Prop (Q)**
(5,1,1,0)	178.489	0.73	0.59
(2,1,1,0)	178.674	0.45	0.85
(4,1,1,0)	180.343	0.48	0.62
(1,0,1,0)	180.461	0.24	0.74
(3,1,1,0)	180.474	0.42	0.89

Table 2. The best combinations of orders for the SARIMA model to fit and forecast the dissolved oxygen time series.

Orders combinations (p, q, P, Q)	AICs	Jarque-Bera (L1) Prop (JB)	Ljung-Box Prop (Q)
(0,2,0,1)	67.162	0.66	0.72
(1,1,0,1)	67.683	0.60	0.87
(0,0,0,1)	67.797	0.58	0.36
(0,1,0,1)	68.074	0.86	0.62
(0,3,0,1)	68.827	0.58	0.49

3. Results and discussion

3.1 Model identification

Implementing the general framework of the study (Figure 3 and Algorithm I) identified SARIMA(5,0,1)(1,0,0)12 and SARIMA(0,1,2)(0,1,1)12 to be the best models for forecasting water temperature and dissolved oxygen concentration in the reservoir, respectively. To evaluate the model efficiency, both datasets were divided into two parts: train and test. The ratios of training data and testing dataset were 75% and 25%, respectively, in order to forecast an entire year which is 2024. For both water quality parameters, the training period stared at (Jan 01, 2021) and ended at (Dec 21, 2023), and the testing period stared at (Jan 16, 2024) and ended at (Dec17, 2024). The models' outputs evaluation against the corresponding observed data are displayed in Table 3, which is the model performance evaluation in the training and testing phases for both SARIMA models. This evaluation process highlighted the model good accuracy due to the low MAEs in capturing each water quality parameter's complex patterns, trend, and seasonality in the study area temporally. The MAEs of the water temperature SARIMA model were 2.384 °C for the training phase and 3.813 °C for testing phase, and they were 1.026 mg/L and 0.445 mg/L, respectively, for the dissolved oxygen SARIMA model. Hence, the very close differences between the metrics in the both phases reveal the good agreement among each model's complexity, bias, and variance (Hyndman & Koehler, 2006; Beyeler et al., 2019). Furthermore, the results of both models' residuals check (Figures 8 and 9) showed good agreement with the SARIMA model residuals assumption of white noise, homoscedasticity, normality, and insignificant autocorrelation (Luo, 2024; Cao et al., 2026). It should be noted that these results are limited by the SARIMA model core assumptions: Data stationarity and linearity in addition to the model residuals assumptions of normality and white noise. Hence, data agreement with the model assumptions is considered crucial criteria for assessing the reliability and validity of the model, as they represent the essential conditions that must be satisfied to get results with good accuracy.

Table 3. The SARIMA models performance for both training and testing phases.

Water quality parameter	Evaluation phase	MAEs
Water temperature, °C	Train	2.384
	Test	3.813
Dissolved oxygen, mg/L	Train	1.026
	Test	0.445

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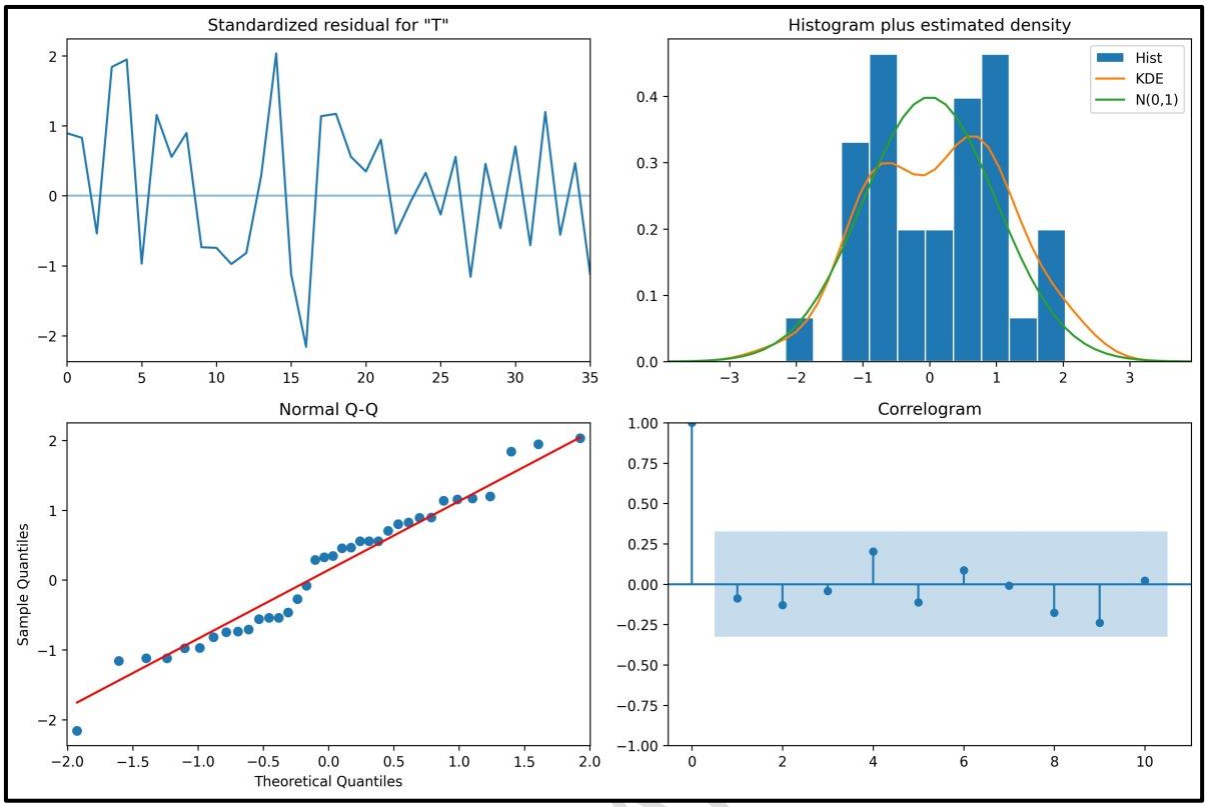


Figure 8. Diagnostic plots for the water temperature SARIMA model residuals.

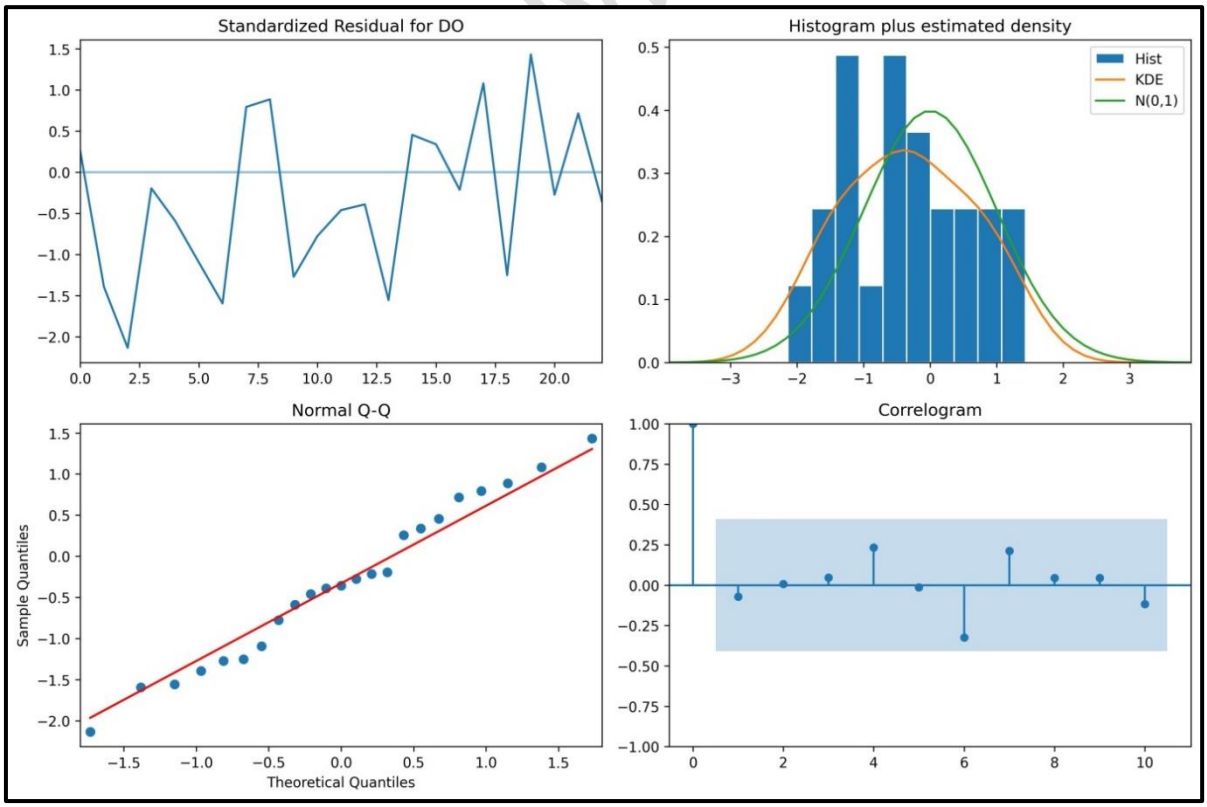


Figure 9. Diagnostic plots for the dissolved oxygen SARIMA model residuals.

3.2 Water temperatures forecasting

The water temperatures model, SARIMA(5,0,1)(1,0,0)12, was run to forecast the reservoir water temperatures over time as displayed in Figure 10. The model's outputs of training phase compared to the observed time series data of water temperatures were plotted in red (Model predictions), while testing phase outputs were plotted in orange (Model forecasts). Obviously, the model results successfully capture the seasonal pattern of water temperatures with low MAEs (Table 3), maintaining same trend between phases. In consequence, the developed SARIMA model of water temperature performed well by accounting for the time series major components of trend, seasonality, and residuals. The results of the developed model indicated that the forecasted values of the temperatures are closed to the measured values. Moreover, the model was validated with good accuracy in predicting the maximum and minimum values of water temperature, reflecting its ability to efficiently capture the monthly variations in water temperature. The good agreement between the forecasted values and measured values also gives an evidence that the time series is stationary, as the statistical properties of the series remained relatively stable over time. The model forecasts indicated that the maximum value of water temperature was 27.790 °C during July, and the minimum value was 18.073 °C during January. Additionally, the maximum amplitude value in forecasted year is slightly lesser than the observed value in that year of the model forecasts, and the minimum value is slightly higher than the observed value. Accordingly, there is evidence that the seasonal structure is maintained during the model forecasts period since the wave amplitudes remain static and consistent with the seasonal wave period

Water temperature is an essential forcing factor of ecological processes in reservoir ecosystems since it shapes seasonal dynamics and biological communities, and controls ecological interactions. Temperature of water strongly controls metabolic rate of the aquatic organisms. Thus, the warm water increases their metabolic activity (Shokri et al., 2024). The reservoir seasonal pattern was characterized in which high water temperatures occur during the hot months (July and August) in summer season, and low values were noticed during the cold months (December and January) in winter season. In summer, higher temperatures increase water column stratification, leading to warmer surface waters and reduction in deep layer mixing. As a result, deeper zones become cooler . This restricts habitat for fish and other organisms that are sensitive to temperature and forces alterations in species distributions and behavior (Carrillo-Longoria et al., 2024; Almeida et al., 2025). In winter, cooler temperatures reduce metabolic rates across aquatic organisms and suppress primary productivity. Seasonal temperature variation affects fish physiology and behavior, such as growth rates, stress responses, and survival boundaries beyond optimal ranges. In addition, plant and phytoplankton community composition also alter leading to direct implications for ecosystem productivity and stability (Zhao et al., 2025; Xiao et al., 2025).

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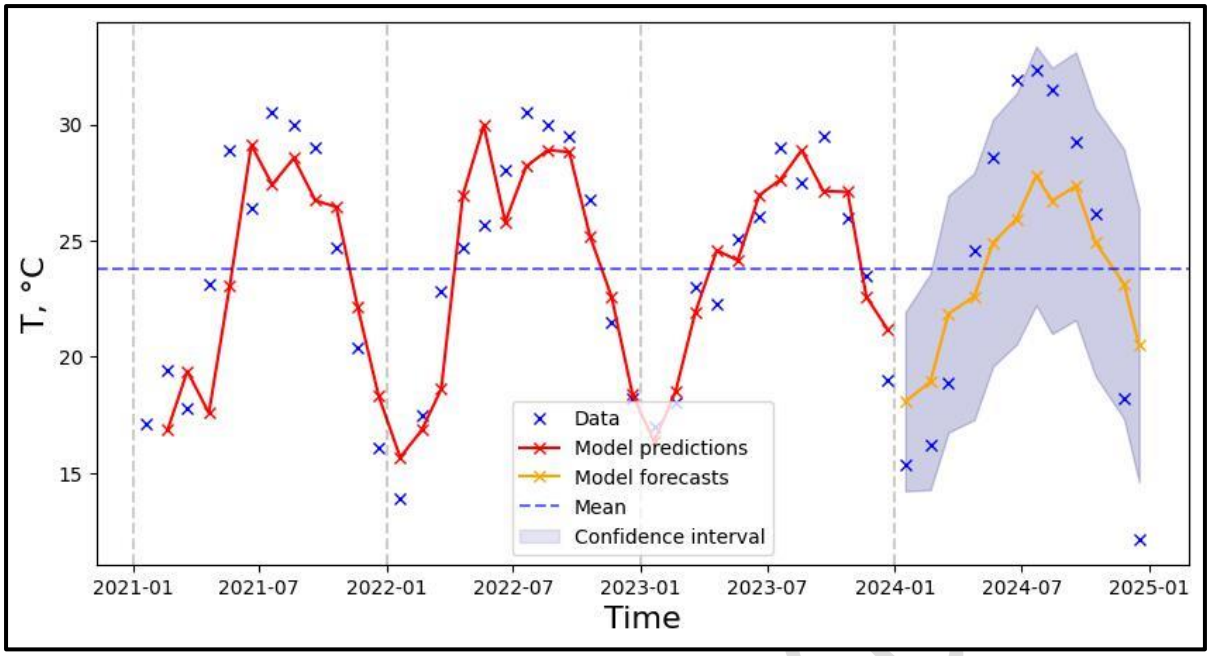


Figure 10. The SARIMA model's outputs of water temperatures compared to the observed field data at Saddat Al-Hindiyah Reservoir during the study period.

3.3 Dissolved oxygen forecasting

Likewise, the dissolved oxygen model's outputs, SARIMA(0,1,2)(0,1,1)12, was displayed as shown in Figure 11, which is a comparison between the model's outputs and the observed data of dissolved oxygen. Good agreement was achieved by the model in term of error statistics during both phases (Table 3). Hence, trend, seasonality, and variation in dissolved oxygen time series were captured efficiently because the outputs of the model strongly correlate the true behaviors and patterns of the real observed data. This firmly supports that the short-term outputs provided by the model is reliable to forecast dissolved oxygen based on univariate time series. The model forecasts curve generally tracks the same pattern of the observed data in the temporal domain. As depicted in Figure 11, the continuous time series reflects the dissolved oxygen's dynamic behavior in the targeted area. The dissolved oxygen concentration reached a minimum value during the summer season (5.078 mg/L), while the maximum value of dissolved oxygen concentration was reached during the winter season (7.643mg/L). Hence, the forecasted concentrations of the dissolved oxygen fall within the range of (5.078- 7.643) mg/L with moderate troughs and peaks, capturing dissolved oxygen concentration trend over the forecasting period.

Results demonstrated obvious seasonal variability, characterized by frequent annual cycles with maximum peaks occurring during months of winter, especially in January, and minimum values during the summer months, mainly in July. This seasonal pattern in the dissolved oxygen time series is physically reliable with the climatic conditions of the targeted area.. The oxygen solubility increases in winter, while it decreases in summer, reducing the dissolved oxygen concentration (Jones et al., 2011; Huang et al., 2021). Clearly, the model forecasted water temperatures and dissolved oxygen concentrations individually in the reservoir waterbody. Figure 12 shows both models' forecasting results, highlighting the clear seasonal interaction between both water quality parameters. However, it's crucial to note that this relationship can be effected by numerous other factors such as biological activity, levels of water quality constituents, flow rates, and conditions of local environment (Bačová Mitková et al., 2024). In addition, the dissolved oxygen forecasting revealed that the

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permissible limits of dissolved oxygen (4 mg/L minimum) weren't violated during the entire study period. Hence, dissolved oxygen normally limits the aquatic health, especially fish and other organisms' lives in surface waters. It is considered as an indicator of water quality in aquatic ecosystems, and the presence of pollutants that deplete oxygen in water increases the ecosystem degradation conditions by reducing available oxygen (Caissie, 2006; Ma et al., 2025; Knoll et al., 2025).

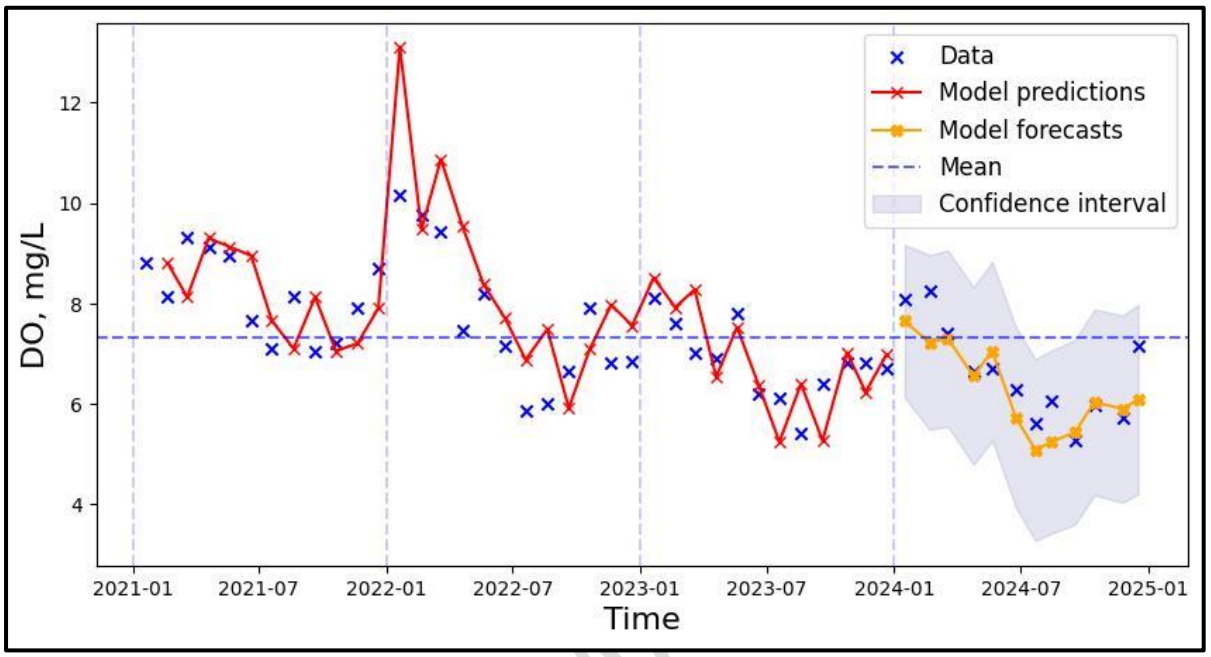


Figure 11. The SARIMA model's outputs of dissolved oxygen compared to the observed field data at Saddat Al-Hindiyah Reservoir during the study period.

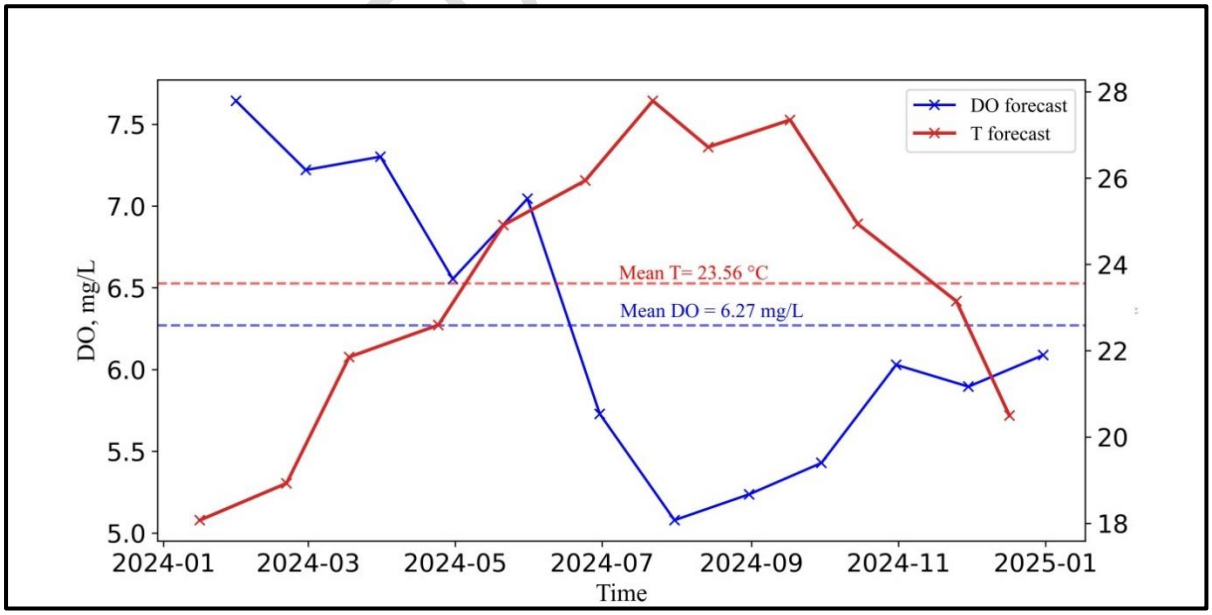


Figure 12. The SARIMA model's forecasting results of water temperatures and dissolved oxygen at Saddat Al-Hindiyah Reservoir.

Consequently, the SARIMA model was effective in handling seasonal patterns of water temperatures and dissolved oxygen time series data for the reservoir. It can accurately capture and analyze various seasonal patterns, providing precise forecasts for seasonal time series when parameters are correctly adjusted. One advantage is that it requires minimum technical expertise from modelers since only one univariate time series is needed to build the model. It is also easier to implement with low computational costs resulting that computing power is highly reduced. The SARIMA model with these features was particularly suitable for forecasting water quality parameters such as water temperatures and dissolved oxygen in surface waters in data-scarce systems. It can still produce rationally accurate predictions by using limited historical data. In addition, the SARIMA model has the ability to exactly learn temporal patterns, trend, and seasonality of dissolved oxygen time series data without other water quality forcing constituents such as water temperatures variation with time. Hence, a single dissolved oxygen time series can be useful for forecasting the dissolved oxygen seasonal dynamics. However, it requires expertise in accurately determining seasonal and non-seasonal component orders, which can complicate the modeling process. It can be particularly complex when multiple seasonal patterns exist, necessitating further analysis and investigation to tune the model optimally. Moreover, the predictive ability of the SARIMA model is commonly limited to short and medium term forecasting and becomes less reliable over the long term (Park, M.-J. & Yang, H.-S., 2024). Nevertheless, the SARIMA model is still a useful tool for management of aquatic ecosystem since it can efficiently extract the temporal patterns and the relationships directly from available data.

4. Conclusions

A SARIMA model was developed and utilized to forecast the temporal dynamics of water temperatures and dissolved oxygen concentrations in Saddat Al-Hindiyah Reservoir, Iraq, based on a four years period univariate time series for each parameter. The main findings showed that the temporal patterns of seasonal fluctuations were effectively captured by the developed models for the both parameters, and a seasonal period length of twelve months occurred every year. The forecasting process gave [T MAEs: 2.384 °C for the training phase and 3.813 °C testing phase] and for dissolved [DO MAEs: 1.026 mg/L for the training phase and 0.445 mg/L testing phase]. Hence, the SARIMA model succeeded in following the temporal patterns, trend, and seasonality of both water temperatures and dissolved oxygen concentrations variation over time. In addition, the SARIMA models' forecasts were subtle in long-lasting the inverse relationship between water temperatures and dissolved oxygen concentrations in the reservoir. Moreover, the dissolved oxygen concentrations in the reservoir were acceptable for aquatic health during the study period (DO $\geq$ 4.0 mg/L). The research acknowledged that the efficient computation of SARIMA model's seasonal and non-seasonal component orders can improve the model accuracy, and therefore the future work may provide other tuning methods to identify the SARIMA model's orders such as using the machine learning techniques. Accordingly, using SARIMA model boosts the extraction of the essential information concerning water temperatures and dissolved oxygen interaction within the water body ecosystem, and it is feasible for the applications of time series forecasting in reservoirs.. Hence, this study demonstrated the potential of univariate forecasting SARIMA models for monitoring water temperatures and dissolved oxygen cost-effectively and efficiently, giving potential early warnings of water quality degradation. The present modeling approach supports the environmental agencies by providing possible supplementary decision support in timely manner. The findings also exhibited the convenience of SARIMA model as an exploratory tool for assessing the reservior potential ecological risk.

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