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Evaluation of some regression models in the prediction of dissolved oxygen and water temperature of the Jarreh Dam, Iran

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ABSTRACT

The climate change phenomenon has resulted in increased unpredictability regarding water availability in dry and semi-dry areas. This challenge affects not just the amount of water accessible but also intensifies worries about the quality of water. Water quality is impacted by climate change, specifically through extreme fluctuations in precipitation and temperature and, consequently, more runoff and evaporation rates. The warmer temperature and less precipitation affect water temperature as well as ecosystem health. It is essential to consider how changes in water temperature (Tw) and dissolved oxygen (DO) levels are influenced by heat exchange with the surrounding environment to evaluate water quality comprehensively. The primary goal of this research is to assess alterations in Tw and DO utilizing regression models within the Jarreh Dam reservoir in southwestern Iran. The findings indicated that air temperature had a considerable impact on Tw, as the large reservoir of the dam reduced the influence of other weather factors and hydraulic conditions on variations in Tw and DO. The accuracy of Tw estimation increased with longer time scales, and using logistic equations further improved this precision. Additionally, the effects of stage fluctuations on Tw and DO were minimal due to slight variations in relative water depth. Consequently, it was essential to consider both the direct effects of temperature and the indirect influences of factors like water salinity when evaluating the impacts of climate change on dissolved oxygen in rivers. Additionally, of the two evaluated chemical parameters, the electrical conductivity model was important because of its impact on biological activities. In large water reservoirs where high turbulence through modifications is unfeasible, considering chemical and biological parameters may be more effective for optimizing DO levels than just adjusting water levels.

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1. Introduction

The volume of withdrawn water and wastewater has notably increased in recent years due to rapid population growth, improved living standards, industrial development, and human activities. In many developing areas, excessive wastewater is directly discharged into surface water bodies without proper treatment. Moreover, agricultural pollutants like fertilizers and pesticides are continually being released into water resources. Additionally, the frequency of droughts has worsened and expedited the deterioration of water resource quality. This situation poses an even greater threat to sustainability than before. Various parameters, such as water temperature (Tw), electrical conductivity (EC), and hydrogen potential (pH), have been considered by experts to evaluate water quality [1]. Among these is analyzing dissolved oxygen (DO), which serves as a key indicator of water quality and is widely used to measure water quality and assess water contamination. It plays a vital role in characterizing aquatic environments, reflecting the balance between oxygen production and consumption in that environment. Predicting its concentration could provide valuable insights for environmental management. Therefore, its accurate measurement and prediction provide a better understanding of the quality of water resources, their proper management, and valuable insights for environmental management [2-4].

In ecosystems, DO concentration is influenced by both physical (e.g., temperature and turbulence) and biological (e.g., photosynthesis and respiration [5]. Managing water bodies involves a critical focus on tackling the decrease in DO levels. This decline often occurs as a result of an overabundance of organic matter and nutrients in the water. In rivers, gas exchange rates are higher than in lakes and estuaries despite the same biochemical processes governing oxygen supply and demand [6]. Anthropogenic activities can cause hydrological changes that result in hypoxia, such as the construction of hydroelectric dams with large reservoirs leading to high nutrient contents [7] and significant water abstraction for purposes like irrigation that result in reduced oxygen supply [8]. A decrease in DO concentration below 2 mg/L leads to hypoxia. In this situation, severe ecological destruction is inevitable [9]. The presence of adequate nutrients is essential for fish growth, and fish ponds are typically fertilized to promote optimal growth or to sustain endangered species in lakes [10]. However, the excessive presence of nutrients diminishes its positive effects and leads to eutrophication in water bodies.

Numerous studies have confirmed the impact of Tw on the concentration of DO. This is primarily due to the impact of Tw on crucial biological processes, such as photosynthesis, respiration, and the breakdown of organic matter [11], all of which are pivotal factors in determining the levels of DO. As a result, climatic conditions, water nutrients [12], and atmospheric physical processes [13] exert indirect but substantial effects on the quantity of DO present in the water. Tw, in turn, is influenced by various meteorological factors and physical characteristics that impact the flow of the river, leading to either cooling or heating of the water. These factors generally result in energy exchanges in water over the long term, such as solar radiation, or over the short term, such as wind speed and air temperature.

Additionally, the Tw of a river can be affected by coastal vegetation (riparian vegetation), the watercourse's geomorphology, and the region's topography [14]. Some anthropologic activities, such as the construction of dams, can exert a significant influence on Tw [15]. The presence or absence of vegetation along riverbanks can also impact Tw [16]. Moreover, adding or withdrawing water, apart from directly affecting Tw, can induce spatial and temporal variations in river Tw by influencing afforestation, deforestation, and air temperature [17].

The modeling of river DO was started about a hundred years ago by Streeter and Phleps (1925) [18]. After examining the processes of deoxygenation and re-aeration, they provided a simple equation to predict the amount of DO and then validated it with data from the Ohio River. Since then, many scientists have derived and introduced different equations between DO and river water quality. Since many factors affecting DO are still unknown, the equations do not have accurate predictions in many cases. In addition, many of these equations require a lot of data for prediction, which are sometimes unavailable, unreliable, or expensive to obtain. In the pursuit of estimating Tw, various physical models have been developed over the years. These models are rooted in the consideration of heat fluxes and radiation interactions among the streambed, air, and water [19]. Given the complexity of measuring these parameters, it becomes imperative to employ simpler models that necessitate less input data. In recent years, there has been growth in the utilization of regression models in various iterations, which rely on readily available data such as air temperature and river flow velocity. Among these variables, air temperature, extensively monitored across different regions, has emerged as a particularly significant factor in the modeling process.

Traditional regression models tend to have less accuracy in fitness compared to modern models; however, these regression models exhibit distinct strengths that have proven valuable in practical applications. Consequently, experts often rely on them and consider them the top choice for forecasting various parameters in environmental engineering [20]. The regression models demonstrate greater stability compared to new models when it comes to the quantity of input variables and the duration of the recorded data sets. In addition, because of its explicit forms, it is more dependable. The regression model must possess less training and knowledge than newer models. Basic regression models, taking into account the constraints of input variables, are the most widely recognized and practical models in applied research among the different regression options. However, the performance of the regression models was inferior compared to the newly developed models. To enhance the accuracy of these regression models, particularly the simpler ones, it is essential to implement various statistical improvement techniques. These methods will aid in refining the models and ultimately lead to more reliable results. The logistic regression models developed by Mohseni et al. (1998) are known for their simplicity and relatively high efficiency [21]. Despite the passage of several years, these equations have found applications in various fields such as climate change, environmental impact, and energy production [22]. Researchers have utilized the Mohseni et al. (1998) model with data at different time intervals [21]. For instance, Basarin et al. [23] used this model to estimate monthly data, Feng et al. [24] for daily data, Arismendi et al. [25] for a seven-day moving average, and Lubega and Steelwall [26] for a 14-day moving average.

In the current study, the fluctuations in Tw and DO levels within the Jarreh Dam reservoir located in southwest Iran were analyzed using regression models. The study also looked into how variations in time scale, climatic conditions, and certain chemical properties impacted fluctuations in both Tw and DO levels.

2. Material and Methods

2.1 Study site

The Zard River watershed, with an area of 882.49 square kilometers, a perimeter of 207.93 kilometers, and a length of 8 kilometers, is located in the southwest of Iran and the east of Khuzestan province. The studied area is one of the sub-basins of the large Marun-Jarrahi watershed in Khuzestan province, which falls between 39' 49'' to 50' 38' 10' E longitude and 31' 22' 78'' to 52' 42 ˚ 31 N latitude (Figure 1). This watershed boasts a variety of urban areas and industrial sectors, notably petrochemical industries and significant agricultural fields, alongside dynamic aquaculture operations that are greatly affected by water quality levels impacting their output. Also, the Shadegan International Wetland is located at the end of this basin, and, therefore, the indicators examined in this study (water temperature and dissolved oxygen) have a significant impact on maintaining its appropriate conditions. Ultimately, this river ends up in the Persian Gulf, and making improvements to its water quality will benefit the overall environmental state of this aquatic environment. Therefore, increasing water quality in the reservoir improves the quality of water received downstream, thereby ensuring the economic and environmental sustainability of urban areas and water bodies.

The land uses of the Zard River watershed include pasture, rainfed agriculture, gardens, and forests. The mountain and hill regions primarily feature forests and pastures, with some arid areas. In contrast, the plateaus and alluvial terraces mainly consist of irrigated and rainfed agriculture. The changes in land cover cause significant changes in air as well as water temperature [27]. Agricultural lands can also be seen in river sediments and river banks. The geomorphology of the basin includes mountainous, hilly, and plain units. The study area has high sedimentation due to sensitive geological formations. Since air temperature, water temperature, sedimentation, and DO all affect each other, it is useful to consider the above-mentioned factors when interpreting the research results [28].

Also, water quality data, including water temperature (Tw), dissolved oxygen (DO), water depth (Stage), sodium absorption ratio (SAL), electrical conductivity (EC), evaporation (EVP), wind speed (W), relative humidity (P), and inlet flow to the reservoir (qin), was used to model Tw and DO. The meteorological data used in this research were obtained from the Ramhormoz synoptic station, and the water quality data were obtained from the dam company, the power plant, and the irrigation networks of Zareh and Jarrahi in the statistical period of 2018 to 2022. Because this meteorological station has a long history of data collection, its data during the study period was almost complete. Water quality data had shortcomings. Nonetheless, due to a lack of proper calibration, outliers were evident in the water quality data utilized at the beginning of the study period. Occasionally, the failure of equipment caused lapses in measuring some quality indicators. The data were sorted, the missing data were checked and reconstructed, and finally, the resulting data were used in different models in daily, weekly, and monthly steps. The data reconstruction method was employed to address the deficiencies identified in the study data following the preparation of statistics related to water quality indices. The statistical characteristics of this data are presented in Table 1.

2.2 Water temperature models

Two different types of models were employed to predict Tw: deterministic models and regression models. Deterministic models rely on heat balance and require knowledge of thermal inputs and outputs, which may not be feasible in many locations. On the other hand, regression models utilize readily available data such as air temperature to estimate Tw and streamflow, making them a more accessible option as these data are frequently measured at various meteorological and hydrometric stations. The simplest method to express the relationship between Tw and other variables, based on data, is the linear regression model:

$$T_w = a_0 + a_1 T_a + \varepsilon \quad (1)$$

These models have been used in numerous studies spanning from earlier research (Caissie, 2006) to more recent investigations [29]. However, many studies do not consider lag due to the linearity of the relationship; some researchers have examined a lag range between 0 and 29 days [22].

Fig. 1. Location of the study area.

Table 1. Minimum, mean, and maximum of the utilized data in the study.

		Min	Mean	Max
Ta	Daily	5.4	45.4	27.83
	Weekly	19.14	36.77	27.78
	Monthly	24.39	30.82	27.87
Tw	Daily	2.58	31.33	19.48
	Weekly	18.33	28.19	23.34
	Monthly	21.9	25.33	23.39
DO	Daily	2.58	5.66	4.11
	Weekly	3.39	4.66	4.11
	Monthly	3.88	4.35	4.11
Stage	Daily	69.13	93.02	79.11
	Weekly	73.49	85.21	79.35
	Monthly	76.56	88.74	79.33
SAR	Daily	0.5	9	0.82
	Weekly	0.64	2.42	0.82
	Monthly	0.73	1.18	0.82
EC	Daily	1790	1710	1527
	Weekly	1319.4	1669.3	1532
	Monthly	1466	1628	1534
Evaporation	Daily	0.7	9.05	28.4
	Weekly	3.5	9.04	14.82
	Monthly	6.90	9.06	10.76
Wind Speed	Daily	1	4.6	7.14
	Weekly	3	4.50	6.48
	Monthly	3.5	4.48	5.4
Relative Humidity	Daily	6.37	37.28	98.37
	Weekly	19.88	37.27	62.06
	Monthly	29.44	37.46	43.61
Inlet Flowrate	Daily	0	5.23	90.17
	Weekly	1.23	5.21	29.71
	Monthly	1.99	5.18	10.65

However, it may be a good estimate of the linear regression temperatures. In extreme temperatures, the linear regression is less efficient. At low temperatures, the presence of ice cover prevents heat exchange; at high temperatures, the presence of water vapor acts as a radiation reflector and prevents water from heating. In both situations, the influence of Tw on air temperature changes decreases [30]. To solve this problem, Mohseni et al. [21] introduced and tested a non-linear regression relationship in weekly time steps. This relationship was widely used and modified in the following years [22,31].Mohseni et al. [21] presented the following relationship to increase the accuracy of Tw estimation:

$$T_w = \frac{\alpha}{1 + e^{\gamma(\beta - T_a)}} \tag{2}$$

In this regard, $T_w$is the water temperature, T_a is the air temperature, α is the estimator coefficient of the maximum Tw, β is the air temperature at the infllection point, and γ is the steepest slope of the logistic function. Microsoft Excel solver was used to determine the coefficients. Taking into account that the studied river does not freeze, the relation (2) can be modified by adding a coefficient μ that estimates the minimum Tw as follows:

$$T_w = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}} \tag{3}$$

The influence of air temperature on Tw is significant, with other meteorological parameters and streamflow also playing a crucial role. Past studies have indicated that incorporating streamflow using multiple regression does not necessarily yield superior results compared to logistic and linear models. In a specific research context, due to the challenges associated with determining streamflow in the reservoir of the dam, flow depth is utilized as a substitute for streamflow in the multiple regression equation.

$$T_w = a_0 + a_1 T_a + a_2 ST + \varepsilon \tag{4}$$

where ST is the stage level corresponding to the Tw.

2.3 Regression models of DO

The simplest model for determining DO using Tw is linear regression and is as follows:

$$DO = a_0 + a_1 T_w + \varepsilon \quad (5)$$

Harvey et al. [32] tested an exponential regression to model DO using Tw in several rivers in Newfoundland and Labrador. In their research, this equation, as follows, has been investigated:

$$DO = e^{(a_0 + b_1 T_w)} \quad (6)$$

Also, multiple regression was used to study the effect of considering SL to improve DO estimation. Its relationship is presented as follows:

$$DO = a_0 + a_1 T_w + SL + \varepsilon \quad (7)$$

2.4 Statistical evaluation

The normalized root mean squared error (NRMSE) and MAE (Mean Absolute Error) were used to compare the accuracy of the relationships used in the estimation of DO in Jarreh Dam water. Any model that has less amounts of the two mentioned measures is more accurate than other models. The following equations describe the method of determining the mentioned indicators:

$$NRMSE = \frac{1}{n}\sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i| \quad (9)$$

where O_i and P_i are the observed and predicted value of Tw or DO, respectively, and $\bar{O}_i$ and $\bar{P}_i$ are the mean observed and predicted of Tw or DO, respectively.

2.5 Study of factors affecting citric acid production

Citric acid production was compared at different factors: various concentrations of nitrogen source (ammonium nitrate (AN) 0.5, 1.0, 1.5%), a carbon source (sucrose and molasses 15,15%), and an alcohol source (methanol 1.0, 2%). All of the experiments were done in duplicate with *A.niger* and *A.tubingensis*.

3. Result and discussion

Over the course of different years, the variations in DO levels showed a nearly identical pattern. Nevertheless, these patterns were not entirely the same. Previous researchers, namely Post et al. [33] and Hu et al. [34] have documented the presence of a pattern in the seasonal variations of Tw and DO (Figure 2. (top)). In December and January, DO levels were at their highest, whereas July and August saw the lowest amounts. The fluctuations in Tw showed a consistent seasonal trend across various years (Figure 2. (middle)). In comparison, the fluctuations in Tw followed a more predictable seasonal pattern than those observed in DO levels. Contrarily, its highest point was seen during the period from July to September, while its lowest point occurred in December. Due to the fact that maximizing DO levels relies on minimizing Tw, it follows naturally that the peaks in temperature and DO occur approximately 6 months apart. Rajesh and Rehana [35] noticed an identical trend in various locations throughout the Ganges River valley. A significant factor in this phenomenon is the decline in gas solubility as temperatures rise [36]. Jane et al. [37] mentioned that external factors could impact this process in either a negative or positive way.

In this study, the stage changes had a seasonal pattern almost similar to the changes in DO concentration (Figure 2. (below)). Despite being distinct each year, the pattern demonstrated a notable increase in alterations during the initial period while showing lesser shifts in subsequent years. Overall, alterations in this stage did not have a notable impact on fluctuations in Tw and DO levels. Therefore, it seems that investigating the effectiveness of annual changes in ST with DO requires data for a longer period of time.

3.1 Water temperature modeling

The solver in Microsoft Excel was employed to determine the parameters of the Tw models. The two goodness-of-fit measures of MAE (Mean Absolute Error) and NRMSE (normalized root mean squared error) were used to assess the precision of the applied models. The results of modeling during calibration and verification are shown in Table 2 for daily, weekly, and monthly periods. The difference between the linear model and the first and second logistic models was found to be insignificant. Upon comparing the three models, it was evident that the second logistic model produced superior results compared to the other two. By investigating 43 rivers spanning 13 countries, it is determined that the implementation of nonlinear regression resulted in more accurate predictions of Tw using air temperature as a variable [38]. In addition to this, Al-Jashaami and Al-Zubaidi [39] observed that the nonlinear logistic function proved to be accurate in determining the Tw of Laurance Lake, Oregon. Nevertheless, they asserted that variations in time did not impact the precision of the resulting model. In contrast, the findings of the current study were in contrast to those found in Harvey's research [40]. Perhaps the reason for this variation lies in the freezing temperatures present in the rivers they analyzed compared to the absence of such conditions in the river under investigation. Indeed, factoring in the minimum temperature as the μ parameter in rivers with temperatures exceeding freezing could lead to improved prediction accuracy. In addition, at high and low temperatures, using the logistic model improves the accuracy of the equation compared to the linear model [40].

If the response variable is categorical, opting for logistic regression instead of linear regression is more favorable due to the absence of restrictions. The superiority of the logistic regression model over the linear regression model lies in its ability to make predictions as probabilities between 0 and 1 without the constraints of normal distribution assumptions. While the linear regression model forecasts values across the spectrum from negative to positive infinity, this approach is not suitable for predicting categorical variables. The logistic regression model is an altered form of linear regression that estimates the likelihood of the output variable based on a linear combination of input variables. However, the logistic regression model may have limitations in estimating DO or Tw values. Generally, the accuracy of predictions made by this model is relatively high, especially in cases where there is a linear relationship between response and explanatory variables [41].

Table 2. Comparison of results of applying different Tw models.

Model	Time Scale	Calibration		Verification	
		NRMSE	MAE	NRMSE	MAE
$T_w = 9.33 - 0.50 \times T_a$	Daily	6.7	1.99	6.9	2.12
$T_w = 10.12 - 0.48 \times T_a$	Weekly	4.0	0.68	4.4	0.86
$T_w = 10.19 - 0.47 \times T_a$	Monthly	2.9	0.36	3.3	0.52
$T_w = \frac{33.46}{1 + e^{0.06(13.95 - T_a)}}$	Daily	6.9	2.23	7.1	2.38
$T_w = \frac{33.85}{1 + e^{0.06(14.42 - T_a)}}$	Weekly	4.1	0.71	4.5	0.92
$T_w = \frac{32.86}{1 + e^{0.07(14.95 - T_a)}}$	Monthly	3.0	0.39	3.3	0.51
$T_w = 15.77 + \frac{31.48 - 15.77}{1 + e^{0.17(28.68 - T_a)}}$	Daily	6.6	1.87	4.8	2.00
$T_w = 18.28 + \frac{28.31 - 18.28}{1 + e^{0.22(27.60 - T_a)}}$	Weekly	4.1	0.71	4.3	0.83
$T_w = 20.29 + \frac{34.48 - 20.29}{1 + e^{0.20(34.62 - T_a)}}$	Monthly	3.0	0.37	3.4	0.55
$T_w = 8.72 + 0.55 \times T_a - 0.08 \times ST$	Daily	6.7	1.98	6.7	2.02
$T_w = 6.92 + 0.76 \times T_a - 0.05 \times ST$	Weekly	2.92	0.38	3.2	0.49
$T_w = 9.67 + 0.51 \times T_a - 0.06 \times ST$	Monthly	4.0	0.68	4.28	0.83

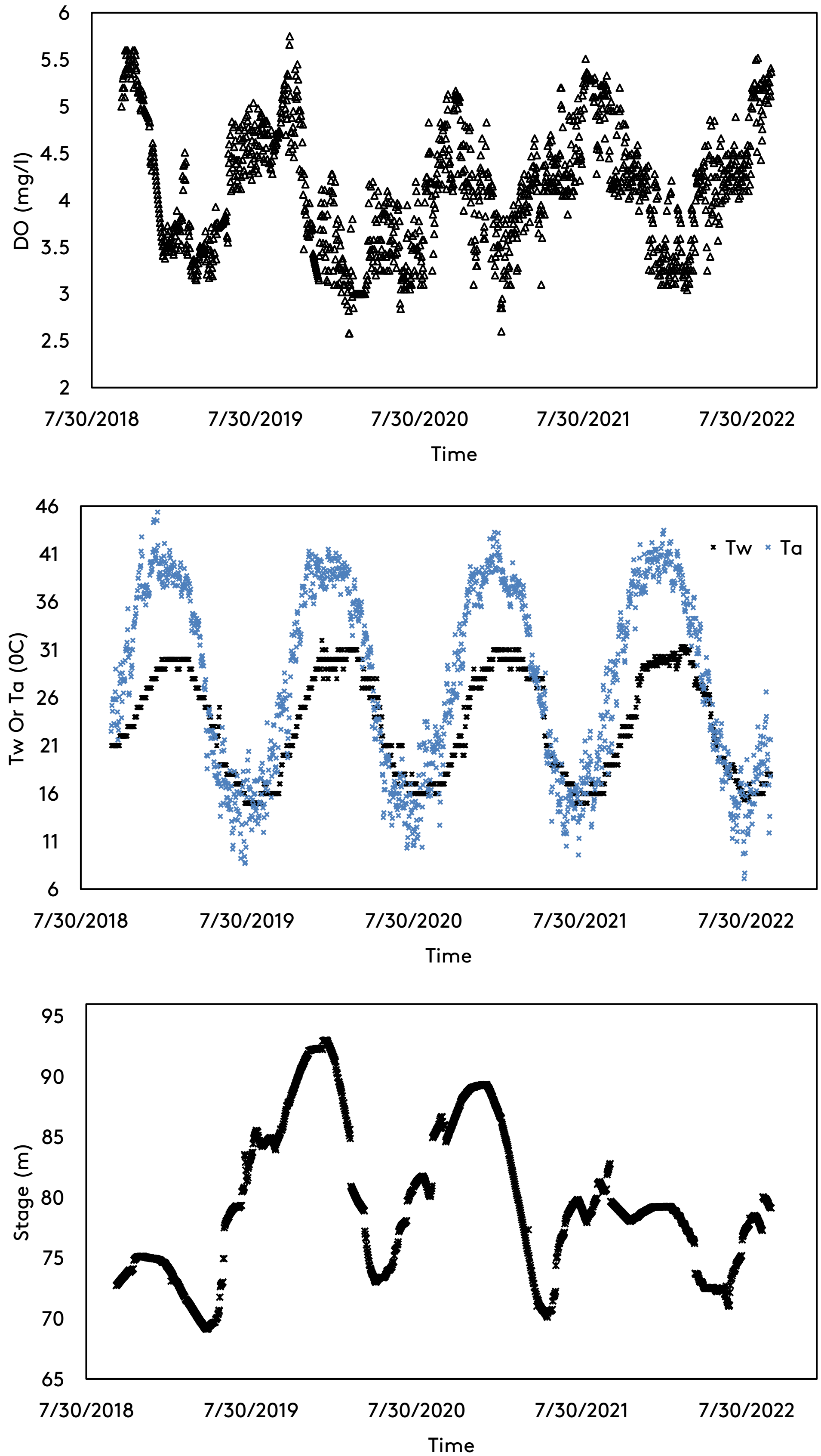

Fig. 2. Variations of DO (top), air and Tw (middle) and Stage (below) from 2018-2022.

In different stations, Tw was measured in various time scales. These intervals ranged from a few minutes to monthly or even seasonal. However, this data may not be measured in many small or seasonal streams [42]. Similar to Erickson and Stefan [43], choosing different time scales resulted in different line slopes and intercepts. Moreover, the findings demonstrated that estimates in both linear and non-linear models became more accurate as the time scale increased. Moving from a weekly to a monthly scale showed a significant increase in accuracy compared to moving from a daily to a weekly. This could be attributed to the greater variability in daily data as compared to the more consistent patterns observed in weekly and monthly data. Moreover, despite the potential of linear models to provide improved predictions at weekly and daily intervals, in extreme cases, non-linear relationships yield more accurate estimates [44]. Some previous studies have noted that stochastic models are better suited for predicting Tw in the short term, whereas regression models are more successful over extended periods [45].

Moreover, despite the stage not showing a significant effect on predicting Tw, its presence in the model did not increase the accuracy of estimation. The primary cause was the minor fluctuations in water levels when compared to the water depths observed in this study. This was similar to the findings of Harvey et al. [32]. However, in contrast to the present research, the relative depth changes were higher in the study mentioned above.

3.2 Effects of the climatological and chemical factors on water temperature

Besides air temperature, factors such as relative humidity and wind speed, as well as the presence of plant canopies, are also significant in determining the heat flux and consequent Tw fluctuations. With little vegetation present near the dam lake throughout multiple seasons, the canopy size is minimal, and its effect is insignificant. In this research, meteorological parameters such as relative humidity, wind speed, and evaporation had no significant effect on Tw (Table 3). In fact, the large volume of the reservoir and, as a result, its great depth has resulted in a low impact of meteorological parameters. Conversely, scientific proof indicates that the reservoir lake works efficiently to balance temperatures by cooling hot summer air and heating cold winter air [46,47].

Two other parameters investigated were the SAR (sodium available ratio) and EC (electrical conductivity) of water. No significant relationship between the SAR and Tw was observed. However, increasing water salinity caused an increase in Tw. This indicates that the dissolution of solids is a temperature-dependent process. The difference observed between EC and SAR results is probably due to the fact that the elements affecting the SAR constituted a small fraction of the dissolved solids in the water. Sibanda et al. [48] also reported a weak positive correlation between EC and Tw (r=0.15).

Table 3. Comparison of the results of utilizing different meteorological and chemical parameters in modeling Tw.

Model	E	NRMSE	MAE
$T_w = 9.66 + 0.48 \times T_a + 0.37 \times SAR$	NS	4.0	0.68
$T_w = 6 + 0.48 \times T_a + 0.002 \times EC$	0.011	4.0	0.67
$T_w = 9.67 + 0.51 \times T_a - 0.06 \times EVP$	NS	4.0	0.68
$T_w = 10.42 + 0.47 \times T_a - 0.07 \times W$	NS	4.0	0.68
$T_w = 8.71 + 0.5 \times T_a + 0.016 \times H$	NS	4.0	0.68
$T_w = 10.08 + 0.47 \times T_a + 0.003 \times q_{in}$	NS	4.0	0.68

Similarly, the effect of EC was not high either. In a similar study, Papafilippaki et al. [49] also observed a positive relationship between water temperature and heavy metal concentrations. However, they did not observe a correlation between EC and heavy metal concentrations. According to the diffuse layer double theory [50], increasing the SAR increases turbidity and thus reduces light penetration in the water, which can affect water temperature. However, increasing salinity can increase flocculation, light penetration, growth of aquatic plants, and temperature by compressing the double diffuse layer. Aquatic organisms may be at risk from high EC levels as they can lead to increased salinity levels in the water and potential suffocation of the stream bottom, particularly in deep waters [48]. Increased salinity levels can potentially cause a rise in Tw, affecting the growth and metabolic processes of aquatic organisms. However, under conditions where temperatures do not reach freezing points, the correlation between salinity levels and increasing temperatures can be attributed to the effect of evaporation on the ion concentration [51].

Investigating the role of inlet flow, researchers explored its effects on heat exchange. The heat flux behavior in relation to flow properties is subject to change based on variations in volume to surface ratio and flow velocity. By constructing dams, the impact of heat exchange due to flow is lessened through the creation of reservoirs and reduced flow velocity [52]. Within this study, it was observed that there was an insignificant relation between the inlet flowrate and Tw as a result of the minimal volume of the flowrate in comparison to the large volume of water in the reservoir. In general, human activities involving building structures such as dams can potentially affect Tw, river flow systems, or both [53].

3.3 Modeling of DO variations

The primary objective of our research was to assess how DO and Tw change over different time scales in order to identify the optimal regression equation. DO changes during the studied period are shown in Figure (1-top). Even though there was a proportional trend between DO changes and both Tw and air temperature, the variability in DO changes was greater than that of Tw. Despite the correlation between the DO changes and Tw and air temperature trends, variability in DO levels could be attributed to additional factors, resulting in a less predictable pattern than that of Tw. The results showed that maximum DO occur at minimum temperatures in the winter, which is the rainy season. This was in contrast to rivers with snow basins, whose minimum Tws occurred during the snowmelt season, early spring. Typically, factors like rainfall, variations in water flowrate, and snow melting can lead to a substantial increase in DO levels when entering the mainstream [54]. The minimal rainfall and lack of snow in the basin, combined with a low inflow-to-reservoir volume ratio, indicated temperature fluctuations as the cause of DO changes.

During the transition from winter to summer, the DO concentration tended to decrease. Consequently, the fluctuations in DO also decreased due to reduced activity of aquatic organisms. Conversely, as summer transitions to the next season, the biological activity of aquatic organisms increases, leading to elevated fluctuations in DO concentration. Processes like photosynthesis, respiration, and mineralization of organic material enhanced the DO levels in water with low flowrates [21]. An increase in biological activities alongside the reservoir's stagnation led to conditions similar to hypoxia [54]. In the Jarreh Reservoir Dam environment, characterized by minimal biological activity, particularly constrained rates of photosynthesis, fluctuations in DO concentrations were primarily influenced by seasonal temperature variations. Nevertheless, other variables could influence these fluctuations and need further investigation. Even though it can be complex to separate the effects of temperature and light in natural rivers [55], controlled rivers, such as dam reservoirs, frequently alter the thermal patterns on their own regardless of light access, making it possible to measure the significance of temperature [56]. One of the recent researches revealed that within the temperature range of 4-45°C, ecosystem-level photosynthesis displayed an exponential increase in correlation with temperature [57].

The comparison between linear and exponential equations showed that the accuracy of these relationships was close to each other. However, the exponential relationship performed slightly better in daily estimation. Also, similar to previous research, due to the variability of DO, the time scale had an effect on it, and the accuracy of the estimates increased as the time scale became larger. In alignment with past studies, the fluctuation of DO was influenced by the length of time considered, leading to a higher accuracy in estimates as the time scale expands (Table 4). Gnauk et al. [58] concluded that on large time scales (more than a week), drastic changes in DO concentration due to temperature changes cannot be recorded by conventional measurement systems. Moreover, considering the stage did not help the accuracy of the DO estimation. Small relative flowrates (small relative stages) affected both Tw and DO [33]. Given the minimal fluctuations in water depth within the reservoir at various time periods, it proved impossible to alter the concentrations of DO. Nevertheless, it appears that the stage has a substantial impact on temperature and DO changes in rivers with shallow depths. Nonetheless, further studies need to be conducted in order to assess the threshold of influence of stage on DO concentration. In addition, similarly to both linear and exponential equations, the precision of the estimations by Equation 5 also improved as the time scale increased.

The division of the data into cold and warm seasons revealed that DO levels decreased as Tw rose in both groups (Figure 3,4). The decrease in DO levels was more severe during the warm season despite both seasons experiencing equal changes in Tw. Consequently, these adjustments were probably the result of a different factor rather than changes in Tw. Changes in DO levels between seasons were possibly due to fluctuating stages caused by shallower water depths in the summer. As per projections of climate change, there will likely be a rise in future air temperatures and Tw. Consequently, there will be a marked reduction in the dissolved oxygen content of the water due to the increase in temperature. Moreover, as a result of the slight fluctuations in water depth and the dearth of water circulation within dam reservoirs, increasing dissolved oxygen to a significant extent is not achievable. Unlike rivers, changes in dam reservoir levels won't bring about an increase in dissolved oxygen content, while purposely fluctuating for this reason may result in a notable loss of stored water. However, this may be done periodically to drain sediments from the reservoir. Among climatic factors, air temperature exerts the most significant influence on fluctuations in water temperature. Consequently, any factor that results in a decrease in air temperature will also result in a corresponding reduction in water temperature. Improving vegetation cover by implementing strategies such as afforestation and conservation measures can help stabilize temperatures in a sustainable manner.

Table 4. Comparison of results of applying different DO models.

Model	Time Scale	Calibration		Verification	
		NRMSE	MAE	NRMSE	MAE
$D_O = 5.81 - 0.072 \times T_w$	Daily	17.5	0.41	17.0	0.40
$D_O = 6.05 - 0.080 \times T_w$	Weekly	10.7	0.15	10.8	0.16
$D_O = 5.87 - 0.070 \times T_w$	Monthly	7.1	0.07	8.3	0.09
$D_O = exp\,[1.81 - 0.017 \times T_w]$	Daily	14.8	0.42	17.0	0.40
$D_O = exp\,[1.88 - 0.020 \times T_w]$	Weekly	10.8	0.15	10.8	0.16
$D_O = exp\,[1.84 - 0.018 \times T_w]$	Monthly	7.1	0.07	8.2	0.09
$D_O = 0.065 - 0.047 \times T_w + ST$	Daily	20.1	0.54	19.0	0.50
$D_O = 0.069 - 0.060 \times T_w + ST$	Weekly	12.3	0.21	12.1	0.19
$D_O = 0.053 - 0.006 \times T_w + ST$	Monthly	8.7	0.10	9.9	0.12

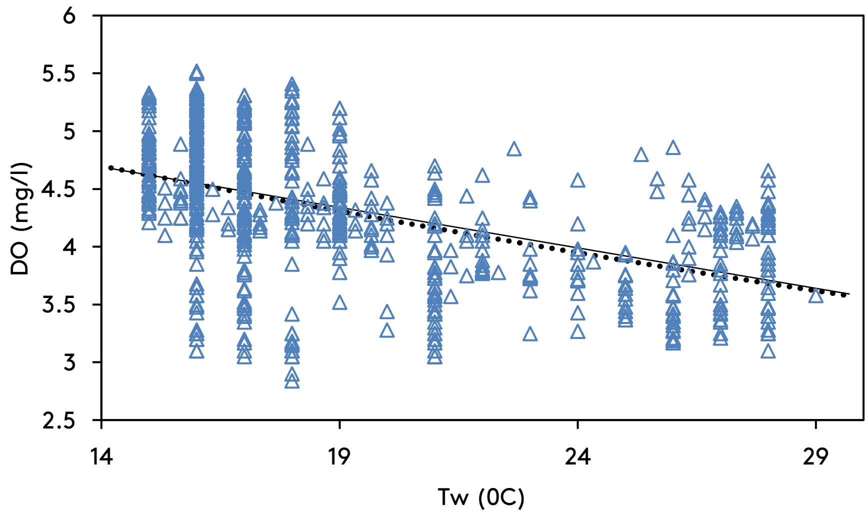

Fig. 3. Daily mean dissolved oxygen in the cooling season fit with a linear regression. DO= 5.67-0.07 (Tw) and exponential regression DO = exp (1.79-0.017(Tw)).

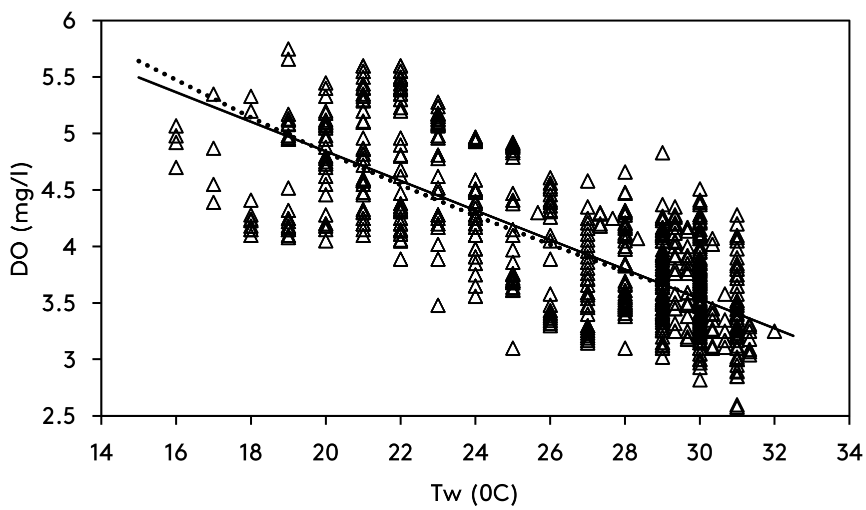

Fig. 4. Daily mean dissolved oxygen in the warming season fit with a linear regression. DO= 7.46-0.13 (Tw) and exponential regression DO = exp (2.19-0.031(Tw)).

4. Conclusions

The Tw has both a direct and indirect impact on the quality of the water and its ecological indicators, such as the concentration of DO. Studying variations in both the DO levels and Tw, in conjunction with meteorological and chemical water parameters, is essential for establishing a comprehensive scientific understanding of the dynamics of natural DO in river systems. The study findings indicated that the DO levels in the river reservoir Jarreh Dam were not impacted by flow and hydraulic conditions but were influenced by temperature variations resulting from seasonal changes. In addition, extending the time scale correlated directly with enhancing the accuracy of Tw estimation equations. Overall, because of the reservoir's conditions and minor water level changes, there was no notable impact on Tw from climatic factors. Because of its impact on biological functions, the rise in electrical conductivity had a direct correlation with temperature. In arid regions, numerous rivers still lack sufficient data for accurately modeling Tw and DO. Gaining a more comprehensive understanding of the factors influencing the fluctuations of these indicators necessitates conducting more thorough and detailed studies.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that would influence this paper.

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