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MODELING RESERVOIR SURFACE WATER TEMPERATURE WITH NEURAL NETWORKS AND ANFIS INSIGHTS FROM SENSITIVITY ANALYSIS

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ABSTRACT

Accurate prediction of reservoir surface water temperature (Tw) is vital for effective water resource planning, environmental management, and maintaining water quality, as Tw impacts numerous physical, chemical, and biological processes. However, in many developing countries, Tw data and related meteorological variables are often scarce. This study assesses the predictive performance of generalized artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) in predicting Tw using a minimal set of climatic inputs and a site-specific cross-validation approach. The dataset was split into two parts: a pooled dataset from six reservoirs in different climatic regions for training, and data from the Beni Bahdel reservoir for testing. Eight input combinations, including air temperatures (mean, maximum, and minimum), relative humidity, and day of the year (DOY), were explored. Both ANN and ANFIS outperformed traditional multi-linear regression (MLR). Among the tested models, those using air temperatures and DOY as inputs, ANN-M2 and ANFIS-M7, showed the best performance, with ANN-M2 achieving an R value of 0.97, RMSE of 1.52°C, and MAPE of 7.43%, and ANFIS-M7 achieving an R value of 0.97, RMSE of 1.54°C, and MAPE of 7.68% during testing. The results highlight that incorporating DOY improves prediction accuracy, and sensitivity analysis identified DOY and mean air temperature as the most important predictors. Overall, ANN and ANFIS offer reliable, user-friendly methods for accurately predicting reservoir Tw, supporting efforts to manage water quality and ecological health in reservoir ecosystems.

Keywords: Surface water temperature, Artificial neural networks, ANFIS, Multi linear regression, Reservoirs.

INTRODUCTION

Water resources are characterized by two key aspects: quantity and quality (Ouis, 2012; Laghzal and Salmoun, 2014; Bouchemal and Achour, 2015; Mohamad et al., 2024). While the water quantity can be easily measured using metrics such as mass, volume, flow rate, or other modern tools (El-Moukhayar et al., 2015; Chibane and Ali-Rahmani, 2015; Bemmoussat et al., 2017; Qureshi et al., 2024), determining water quality is more complex, required sometimes the use of AI, integrated approach, and monitoring system (Abbasi and Abbasi, 2012; El-Kharmouz et al., 2013; Belhadj et al., 2017; Singh et al., 2022; Pandey et al., 2022). Water quality is determined by statistical approach (Lachache et al., 2024), various physical, chemical, and biological factors, with surface water temperature being one of them. Several methods, available in the literature, can be used to improve water quality, hence public health (Faye, 2017; Baba Hamed, 2021; Ihsan and Derosya, 2024; Chadee et al., 2024).

Surface water temperature (Tw) is of great importance physical parameter used in water resource planning and management, as Tw affects physical and biogeochemical processes that occur within the water bodies (rivers, lakes and reservoirs) (Boutoutaou et al., 2020; Sourogou et al., 2021; Mezenner et al., 2022; Chow and Teo, 2023; Mehta et al., 2023; Verma et al., 2023; Trivedi and Suryanarayana, 2023; Shaikh et al., 2024; Panchal and Suryanarayana, 2025). Indeed, Tw influences water quality and biological distribution (Moreno-Ostos et al., 2008), reaeration process at the water-air interface (Nguyen et al., 2014), dissolved oxygen levels, chemical reaction, and growth rates and mortality of aquatic plants and animals (Gooseff et al., 2005). The role of water temperature in eutrophication is both physical and biological. Water temperature strongly influences algal growth rates, nutrient recycling kinetics and biological decomposition (Jørgenson et al., 2013; Ji, 2017). For these reasons, accurate determination of surface water temperature (Tw) is relevant given its importance to aquatic ecosystem health and water quality, and even on the effectiveness of water treatment processes (Ghomri et al., 2013; Khelili et al., 2024; Berafta et al., 2025; Ihsan, 2025).

There are two ways to determine the surface water temperature (Tw). First, measure the water temperature with a sensor. Second, water temperature is assessed using different types of models. Measuring water temperature is the best way to get water temperature data. Despite recent technological developments in measuring instrumentation have made Tw monitoring practical and inexpensive (DeWeber and Wagner, 2014), it is still difficult to obtain Tw data for shorter time step (Day, week) due to fact that water temperature data are measured once a month in Algeria. In addition, the lack of Tw data for some reservoirs due to logistical impediments and limited financial resources allocated for the water quality monitoring program. This results in the loss of temporal variation of TW data and the absence of Tw data for some reservoirs. Therefore, it is important to develop a general model to predict surface water temperature for unsampled time periods or for unsampled reservoirs is of paramount importance.

The dynamics of reservoir water temperature are highly complex and nonlinear, influenced by a variety of factors. These factors include meteorological variables, such as air temperature, relative humidity, wind speed, sunshine duration, and solar radiation, as well as topographical characteristics like altitude, latitude, and longitude. Hydrological conditions, including inflow and outflow, and human interventions such as reservoir management and regulatory practices (Quan et al., 2020), also play significant roles. Additionally, the water body's morphology, including its size and depth (Xenopoulos and Schindler, 2001), further complicates the process. The interaction of these diverse factors poses considerable challenges to developing models capable of accurately predicting water temperature (Tw) in reservoirs. Recently, researchers have developed and applied different types of models to predict water temperature (Tw) in reservoirs (Quan et al., 2020; Wang et al., 2022). In general, these models fall into two main categories: process-based models and data-driven models (Wang et al., 2022). Process-based or deterministic models rely on physical principles and fundamental equations that describe changes in water temperature over time based on appropriate assumptions and boundary conditions (Quan et al., 2020). They require large amounts of accurate data to calibrate model parameters (Mulia et al., 2015), such as lake water depth, inflow and outflow conditions, and meteorological variables (Zhu et al., 2020), which limit their application. In fact, collecting these inputs is time-consuming and sometimes difficult to obtain (Razavi et al., 2012). Common process-based models are CE-QUAL-W2 (Shaw et al., 2017), The Delft3D (Wang et al., 2022), and Environmental Fluid Dynamics Code (Ji, 2017).

In contrast, data-driven models are able to represent linear and non-linear relationships incorporated into the dataset and learn these relationships directly from the data they are modeling rather than using complicated equations (Mulia et al., 2015; Zaidi et al., 2023). Data-driven models include ANN, ANFIS (Ansari et al., 2024), Support Vector Machines, Regression trees, Random Forest, etc. (Fellous et al., 2023). Various authors have used ANN for predicting Tw for rivers (DeWeber and Wagner, 2014; Zhu et al., 2019), lakes (Liu and Chen, 2012; Heddam et al., 2020) and reservoirs (Kimura et al., 2021).

Quan et al. (2020) utilized measured reservoir water temperature data to train a support vector regression (SVR) model and an improved support vector machine (M-GASVR) optimized with a genetic algorithm (GA). Their results indicated that the GA-SVR model outperformed both the SVR and ANN models based on performance metrics in the Longyangxia Reservoir, China. While Wang et al. (2022) proposed a Long Short-Term Memory (LSTM) model trained with data generated by a Delft3D hydrodynamic model and tested it with measured data to solve the problem of missing data at the spatial and temporal levels. The findings revealed that the LSTM model was highly effective in predicting the Tw simulated by Delft3D, achieving an R^2 value of 0.99. Additionally, the R^2 between the LSTM predictions and observed measurements exceeded 0.9.

Many machines learning studies modeling water temperature in lakes and reservoirs have relied on locally trained (site-specific) models (Heddam et al., 2020; Quan et al. 2020; Wang et al., 2022). While effective within limited areas, these models have reduced accuracy when applied to locations outside the original development site. This is a key drawback of small-scale models, they are highly site-specific, meaning their applicability is restricted to the location where they were trained, limiting their generalization to new, untested areas (Ferreira et al., 2019). A more generalized model can be developed by training on data from multiple locations, covering a larger area, to better capture and map the water temperature (Tw) process.

Algeria is a vast country (2,381,741 km²) with a wide variety of climatic zones, microclimates, and soils. The water sector includes 82 reservoirs located in different regions such as humid, sub-humid, arid, and semi-arid zones.

Various studies have examined different aspects of reservoirs in Algeria, including sedimentation, often called siltation (Remini and Remini, 2003; Larfi and Remini, 2006; Remini and Bensafia, 2016; Remini et al., 2019; Jha et al., 2024), specific erosion in reservoir watershed (Bougamouza et al., 2020; Toumi and Remini, 2020; Femmam et al., 2025), reservoir evaporation (Marouane et al., 2024), and water quality (Achour et al., 2019; Madene et al., 2023), and solid transport using ANNs (Bougamouza et al., 2022). However, to the best of our knowledge, no study in the existing literature has investigated water temperature modeling using ANN and ANFIS in Algeria. Therefore, developing a general model trained on nationwide data using limited meteorological parameters would be crucial, useful, and beneficial for predicting surface water temperature (Tw) in reservoirs across Algeria.

Due to the complexity, non-linearity of Tw process, and the shortcomings of process-based models in terms of input data required, artificial neural networks (ANNs) and ANFIS were selected as good candidates to solve the above problems.

Regarding the nature of the dataset used in this work, which is scattered in time (sampling procedure problem) and space (data from seven reservoir), we chose to use feed-forward neural networks, because we seek to map the static relationship among meteorological variables and the corresponding water temperature (Tw). This allows predicting water temperature from meteorological variable, filling the gaps in historical records resulting from sampling program, simulating Tw data for unsampled reservoirs and forecasting the future values of Tw from the national weather forecasts.

This paper aims to: (1) develop generalized machine learning models for predicting reservoir surface water temperature across the country using a limited set of meteorological variables, (2) demonstrate the effectiveness of ANN and ANFIS techniques in practical issues for assessing surface water temperature in reservoirs, and (3) identify the main important predictors through sensitivity analysis.

STUDY AREA AND DATA COLLECTION

This study assessed the performance of the proposed machine learning models using monthly surface water temperature data from eight reservoirs located in various regions of Algeria, provided by the Algerian National Water Resources Agency (ANRH).These reservoirs, characterized by diverse hydrological, morphological, and climatological conditions, were used to ensure the generalizability of the models to new reservoirs in Algeria through a site-based cross-validation approach.

The data was divided into two sets: the first included six reservoirs from various climatic regions, used for model training; the second comprised the Beni Bahdel reservoir with five years of data for model testing. A detailed summary, including periods of data availability and repartition of reservoirs, is provided in Table 1 and Fig. 1.

Table 1: Morphometric parameters of the studied reservoirs (tr: training; tst: test; m.a.s.l: meters above sea level)

Reservoirs	Catch ment area (Km^2)	Crest length (m)	Dam height (m)	Crest level (m.a.s.l)	initial capacity Hm^3	Climate region	Dataset period (used for)
Harbil	180	360	57	208.5	40	Sub humid	2008-2011 (tr)
Keddara	93	468	106	145	145.6	Sub humid	2008-2011 (tr)
Ouizert	2100	950	60	448	100	Semi-arid	2008-2011 (tr)
Bouhanifia	7854	496	54	295	73	Semi-arid	2008-2011 (tr)
Tichy-Haf	3980	275	83.5	294.5	80	Humid	2011-2012 (tr)
Lakehal	189	630	45	684.4	30	Semi-arid	2008-2011 (tr)
Beni-Bahdel	1.016	315	55	664	63	Semi-arid	2008-2012(tst)

The meteorological datasets were collected from the weather stations closest to each reservoir. These datasets include daily climatic variables such as air temperatures (mean, maximum, and minimum); wind speed at 2 meters height (U2); relative humidity (RH); and rainfall. In total, 341 samples were gathered. Additionally, the day of the year (DOY) was used as an auxiliary input, following the approach of Qiu et al. (2020) and Yousefi and Toffolon (2022). The DOY, which ranges from 1 to 365, corresponds to the specific day of sampling, with one value recorded per month for each reservoir. It’s important to mention that the daily meteorological data coincide the days of measurement of reservoirs surface water temperature.

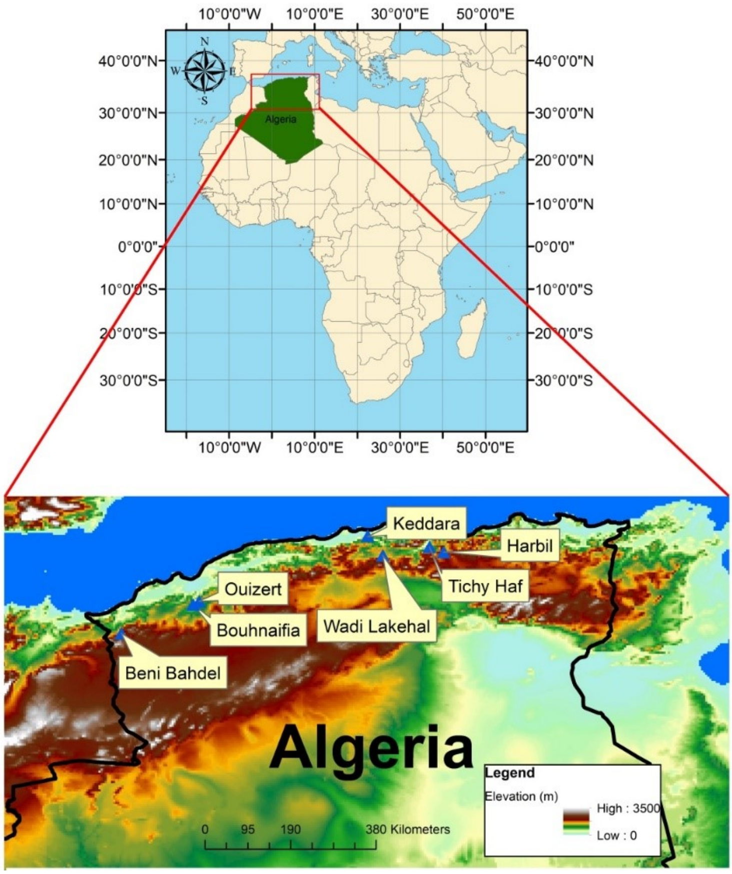


Figure 1: Location of the eight studied reservoir considered in this study

METHODOLOGY AND MODEL DEVELOPMENT

In this study, the modeling of reservoir surface water temperature (Tw) was conducted using MATLAB R2020a, where three scripts were developed to implement and evaluate Multi-Linear Regression (MLR), Artificial Neural Networks (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) models. The dataset was divided into two subsets: a pooled training dataset combining observations from six Algerian reservoirs located in distinct climatic regions, and an independent testing dataset from the Beni Bahdel reservoir. This design allowed for evaluating the generalization ability of the models in a cross-site testing framework. Model performance was assessed using three statistical metrics: the correlation coefficient (CC), root mean square error (RMSE), and mean absolute percentage error (MAPE). Additionally, sensitivity analysis was performed to identify the most influential input variables, using a leave-one-out approach in which each input was systematically removed to evaluate its impact on model accuracy. The following sections present a concise overview of the ANN and ANFIS models, the performance metrics used for evaluation, and the sensitivity analysis conducted to assess input variable importance.

Artificial neural networks (ANNs)

ANNs are complex computational frameworks that take inspiration from the structure and function of biological neural systems (Kordon, 2009; Kouloughli and Telli, 2023). These networks consist of elements called neurons, linked through adjustable connections known as synaptic weights. These weights control the intensity of the connections between neurons, adapting during the learning phase to enable the network to identify patterns in the data. This adaptive capability is a key advantage of ANNs, allowing them to model and interpret the behavior of intricate systems. One of the most commonly used ANN structures is the Multilayer Perceptron (MLP), which features an input layer, one or more hidden layers, and an output layer. In this architecture, neurons in each layer are fully connected to the neurons in the subsequent layer, facilitating signal transmission from the input to the output (Landeras et al., 2008).

In this study, MLP-ANN models comprising an input layer, a single hidden layer, and an output layer were implemented. The optimal number of neurons in the hidden layer (ranging from 1 to 30) was determined by trial and error (Heddam, 2019). The networks were trained using the Levenberg-Marquardt optimization technique, with a sigmoid activation function, and the training continued for 1000 epochs (Tabari et al., 2011).

Adaptative neuro-fuzzy inference system

The Adaptive Neuro-Fuzzy Inference System (ANFIS), developed by Jang (1993), integrates the learning strengths of neural networks with the transparent reasoning of fuzzy logic into a single framework. ANFIS functions as a five-layer network grounded in the Sugeno fuzzy inference model, employing fuzzy if-then rules to approximate nonlinear relationships (Araghinejad, 2014). The system's operation involves two main phases: estimating parameters and identifying structure. The rule parameters -both those related to the premises and the consequences- are fine-tuned using a hybrid approach. This approach involves backpropagation for adjusting premise parameters and the least squares method for refining the consequent parameters (Jang, 1993).

Rather than using traditional grid partitioning, ANFIS structure identification is achieved through subtractive clustering (SC), which offers greater efficiency (Heddam et al., 2012). The key variable in SC is the radius of influence (r), which directly impacts the rules number generated, larger values of r lead to fewer rules. The optimal value of r was determined through trial-and-error, testing values between 0.1 and 1 in increments of 0.01. More details are presented in Zhu et al. (2019) and Kantharia et al. (2024).

Model performance indicators

The performance of three models -MLR, ANN, and ANFIS- in predicting reservoir surface water temperature was evaluated using three key metrics: the root mean square error (RMSE), the correlation coefficient (R), and the mean absolute percentage error (MAPE). These metrics were calculated by comparing the observed surface water temperatures with the predicted values. They were calculated using the following equations:

$$R = \frac{\frac{1}{N}\sum(Oi - Om)(Pi - Pm)}{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(Oi - Om)^2}\sqrt{\frac{1}{N}\sum_{i=1}^{n}(Pi - Pm)^2}} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Oi - Pi)^2} \tag{2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|O_i - P_i\right|}{O_i}\right)\times 100 \tag{3}$$

Where N is the number of samples, O_i is the observed value and P_i is the predicted value, O_m and P_m are the means of O_i and P_i.

Sensitivity analysis

Sensitivity analysis offers a comprehensive evaluation of how changes in input variables affect the output (water temperature), providing essential insights for further analysis and decision-making. It helps classify input variables according to their relative contribution to the output. Various methods are used for sensitivity analysis, and in this paper, the "leave-one-out" approach was applied. In this method we first trained a full artificial neural network (ANN) model using all available input variables. Then, we systematically removed one input at a time and trained a pruned model. The sensitivity of each input was quantified by calculating the ratio of the RMSE of the pruned model to the RMSE of the complete model. This method allowed us to assess the relative influence of each input variable on model performance. A higher RMSE ratio indicates greater importance of the removed input. The ratio is calculated as follows:

$$\text{Ratio} = \frac{RMSE_{\text{Pruned model}}}{RMSE_{\text{Complete model}}} \tag{4}$$

The variables are then ranked based on their ratios, with the highest ratio receiving the top rank (Olszewski et al., 2008).

RESULTS AND DISCUSSION

Seasonal dynamics of water temperature

Fig. 2 represents the 3D surface plot of water temperature (Tw) versus mean air temperature (Tmean) and day of the year (DOY) for 7 Algerian reservoirs. It highlights a clear seasonality, with both temperatures rising from DOY 0 to 300 and falling from DOY 300 to 365. This pattern reflects the Mediterranean climate's hot, dry summers and mild, wet winters. The close correlation between Tw and Tmean indicates that air temperature significantly influences water temperature. Variations among humid, sub-humid, and semi-arid bioclimatic stages affect the amplitude and timing of these temperature changes. These seasonal dynamics are critical for reservoir management, predicting water quality, and understanding ecological impacts in these regions.

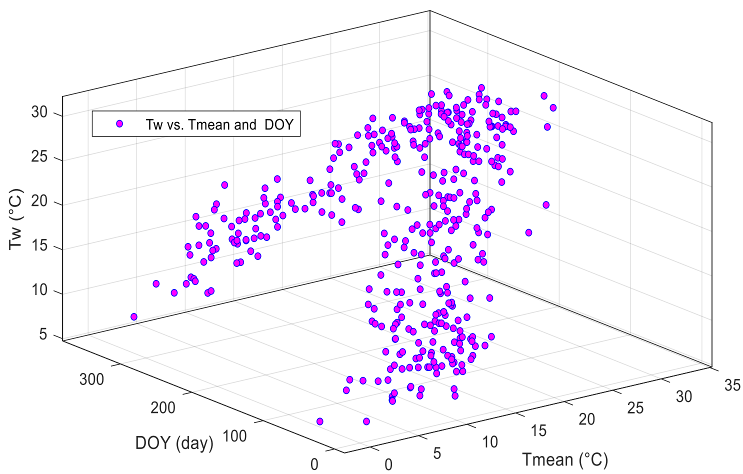


Figure 2: Surface plot of Tw versus T_{mean} and DOY for 7 reservoirs

Inputs selection

In this study, linear correlation analysis was employed to identify the meteorological variables that influence water temperature, offering a straightforward method for selecting relevant inputs. Table 2 shows the correlation between surface water temperature and various meteorological factors, including air temperatures (mean, minimum, and maximum), relative humidity, rainfall (P), and wind speed. The day of the year (DOY) was also used as an additional input. As indicated in Table 2, air temperatures (mean, maximum, and minimum) exhibit the strongest correlation with surface water temperature, highlighting air temperature as the key influencing variable. These findings align with those of Yang and Luo (2020), who also reported a high correlation between air and surface water temperatures. Additionally, we observed moderate, negative correlations between relative humidity and surface water temperature, likely due to the heat loss from the water surface through the evaporation process. This finding aligns with those of Yousefi and Toffolon (2022) who find that correlation between Tw and relative humidity (RH) is -0.27.

The DOY (day of the year) shows a moderate correlation with surface water temperature, with a correlation coefficient of 0.3678. This indicates that seasonality plays a role in influencing surface water temperature. In fact various authors have used DOY as an additional input for modeling surface water temperature in river (Zhu et al., 2019) and lake (Yousefi and Toffolon, 2022). In contrast, rainfall and wind speed exhibit very weak correlations with surface water temperature and were therefore excluded from the input dataset.

Table 2: Correlation between meteorological variables and water temperature (DOY; Day of the year)

	T_{max} (°C)	T_{min} (°C)	T_{mean} (°C)	RH (%)	P (mm)	U_2 (Km/h)	DOY
Tw(°C)	0.8365	0.8045	0.8673	-0.4960	-0.1450	-0.041	0.3678

Correlation analysis revealed that air temperature variables (Tmean, Tmax, Tmin), relative humidity (RH), and the day of the year (DOY) are important input factors for modeling reservoir surface water temperature. Several combinations of these inputs were then tested to find the optimal configuration. Table 3 presents different input variable combinations used for developing the models.

Table 3: Inputs combinations

Combinations	Inputs
M_1	[T_{mean}]
M_2	[$T_{mean.}$ DOY]
M_3	[$T_{mean.}$ RH]
M_4	[T_{mean}. T_{max} and T_{min}]
M_5	[$T_{mean.}$ RH and DOY]
M_6	[T_{mean}. T_{max}. T_{min}. and RH]
M_7	[T_{mean}. T_{max}. $T_{min.}$ and DOY]
M_8	[T_{mean}. T_{max}. T_{min}. RH and DOY]

Models' performance for predicting surface water temperature

The MLR, ANN, and ANFIS models were developed using eight different input combinations to predict surface water temperatures (Tw) in reservoirs. Table 4 provides a summary of the models' performance, displaying key metrics such as the correlation coefficient (R), RMSE, and MAPE. The training phase utilized combined data from six reservoirs, while the testing phase used data from the Beni Bahdel reservoir. The best-performing results are highlighted in bold.

To ensure the generatability of the models to new reservoirs in Algeria, we have used the site-based cross-validation approach. The data was split into two datasets, the first involving the data of six reservoirs located in different climatic regions and used to create data-driven models. The second involves the data of the Beni Bahdel reservoir, which have a length five years and used to test the models.

Table 4 shows that the MLR models yield unsatisfactory results during training and testing. In the testing phase, the correlation coefficient (R) ranges from 0.92 to 0.94, while the root mean square error (RMSE) varies between 2.29 and 2.60°C. The mean absolute percentage error (MAPE) falls between 12.46% and 13.53%. There is minimal variation in accuracy across the different MLR models. Notably, incorporating the time component (DOY) in models M2 and M5 does not enhance their performance. This indicates that MLR models are inadequate for accurately predicting surface water temperatures.

Training results for the ANN models (Table 4) revealed variations: correlation coefficients (R) fluctuated between 0.86 (ANN-M1) and 0.91 (ANN-M5), RMSE values varied from 2.58 °C (ANN-M5) to 3.18 °C (ANN-M1), and MAPE percentages ranged from 7.43% (ANN-M2) to 11.59% (ANN-M6).

During the test phase, for the ANN models (Table 4), the correlation coefficient (R) ranged from 0.93 for ANN-M6 to 0.97 for ANN-M2. The RMSE values varied between 1.52 °C for ANN-M2 and 2.35 °C for ANN-M6, while the MAPE ranged from 7.43% in ANN-M2 to 11.59% in ANN-M6. Consequently, ANN-M2, which uses Tmean and DOY as inputs, delivered the best performance, while ANN-M6, incorporating Tmean, Tmax, Tmin, and RH, showed the weakest results.

Comparable findings were reported by Hadzima-Nyarko et al. (2014), where the authors successfully predicted daily river water temperatures in Croatia using a multilayer perceptron neural network. The root mean square error (RMSE) during the testing period ranged from 1.57°C to 2.74°C.

Table 4 demonstrates that ANN models using only air temperature inputs (M1 and M4) exhibit moderate performance during the test period. This is due to the fact that Tmean, Tmin, and Tmax alone are insufficient to capture the full variability in surface water temperature when using the ANN technique. The ANN-M3 model results show that including relative humidity (RH) alongside Tmean leads to only a slight improvement in accuracy over the ANN-M1 model, indicating that RH has a limited impact on predicting surface water temperature (Tw).

Additionally, the table shows that including RH alongside Tmean, Tmin, and Tmax in ANN-M6 does not enhance the model's accuracy. This is due to the relatively weak and negative correlation between RH and Tw. However, when DOY is added to the air temperature dataset (Tmean, Tmax, and Tmin), the models show significant improvements. Specifically, the RMSE of ANN-M2 shows a 27% improvement compared to ANN-M1 during the test period, while MAPE improves by 32.88%. Similarly, the RMSE of the ANN-M7 model records a 15.9% improvement compared to ANN-M4, with MAPE improving by 13.62%. These results align with the findings of Zhu et al. (2019) and Qui et al. (2020), who showed that including DOY in the input data notably enhanced the accuracy of ANN models.

Table 4: Performance metrics of the developed models for different input combinations

Models	Training			Testing		
	CC	RMSE (°C)	MAPE (%)	CC	RMSE (°C)	MAPE (%)
MLR						
M1	0.8514	3.2779	15.7752	0.9451	2.2931	12.4618
M2	0.8622	3.1653	14.4843	0.9246	2.4789	12.7009
M 3	0.8548	3.2433	15.5145	0.9430	2.3414	12.7312
M 4	0.8548	3.2433	15.5145	0.9430	2.3414	12.7312
M 5	0.8688	3.0948	14.1122	0.9277	2.5666	12.9596
M 6	0.8635	3.1516	14.8769	0.9464	2.4958	13.5310
M 7	0.8636	3.1506	14.4443	0.9261	2.4877	12.8531
M 8	0.8708	3.0726	13.9097	0.9298	2.6069	13.4195
MLPNN						
M1	0.8605	3.1848	15.3467	0.9517	2.0804	11.0824
M2	**0.8999**	**2.7418**	**12.4627**	**0.9745**	**1.5200**	**7.43810**
M 3	**0.8719**	**3.0760**	**14.3629**	**0.9564**	**2.0012**	**10.1233**
M 4	**0.8774**	**3.0220**	**13.9632**	**0.9402**	**2.1293**	**10.3244**
M 5	**0.9128**	**2.5866**	**11.6373**	**0.9502**	**2.0014**	**9.38763**
M 6	0.8808	2.9961	13.5794	0.9372	2.3532	11.5924
M 7	**0.9026**	**2.8719**	**12.5369**	**0.9629**	**1.7904**	**8.91750**
M 8	**0.9112**	**2.7639**	**12.3074**	**0.9588**	**1.7188**	**7.74420**
ANFIS						
M1	0.8612	3.1764	15.3975	0.9501	2.1243	11.3775
M2	**0.9012**	**2.7077**	**12.4696**	**0.9720**	**1.5914**	**8.14780**
M 3	0.8752	3.0231	14.5552	0.9526	2.2363	11.8463
M 4	0.8686	3.0961	15.0500	0.9441	2.1923	11.1610
M 5	**0.9126**	**2.5545**	**12.1237**	**0.9668**	**1.7268**	**8.24725**
M 6	0.8815	2.9508	14.2273	0.9442	2.3629	12.1820
M 7	**0.9087**	**2.6079**	**12.2417**	**0.9719**	**1.5415**	**7.68039**
M 8	**0.9361**	**2.1983**	**10.6913**	**0.9300**	**2.3648**	**10.6860**

During the training phase, the ANFIS models produced correlation coefficients ranging from 0.86 (ANFIS-M1) to 0.93 (ANFIS-M8). The RMSE values varied between 2.19 °C (ANFIS-M8) and 3.17 °C (ANFIS-M1), while the MAPE ranged from 10.69% (ANFIS-

M8) to 15.39% (ANFIS-M1), indicating that some models achieved strong predictive performance whereas others yielded comparatively lower accuracy.

Table 4 shows also the performance of the ANFIS models. The correlation coefficient (R) during testing ranged from 0.93 to 0.97, while MAPE values were between 7.68% and 12.18%, and RMSE varied from 1.54°C to 2.36°C. The ANFIS-M7 model, using Tmean, Tmax, Tmin, and DOY, performed best. It achieved an R value of 0.9719, an RMSE of 1.54°C, and a MAPE of 7.67%. The next best models were ANFIS-M2 (using Tmean and DOY), followed byANFIS-M5, and ANFIS-M8 (using all inputs) respectively.

Similar results were reported by Zhu et al. (2019), where the authors used ANFIS-SC to predict river water temperature (Tw) using mean air temperature (Tmean), river flow discharge (Q), and the Gregorian calendar as input variables. For the Botovo station in Croatia, the RMSE ranged from 1.429°C to 2.35°C in test period.

Like the ANN models, the ANFIS models that use air temperature as inputs (M1 and M4) did not produce satisfactory results. This is because air temperature alone cannot account for all the variability involved in the water temperature (Tw) process. Similarly, the ANFIS models incorporating both air temperature and relative humidity (M3 and M6) also did not perform well. The combination of these two variables was insufficient to fully explain the variations in water temperature.

As observed in ANN models, incorporating DOY (Day of Year) in different combinations substantially improves the performance of ANFIS models. Specifically, the ANFIS-M2 model achieves a 25.08% reduction in RMSE, alongside a 28.38% improvement in MAPE. Similarly, the ANFIS-M7 model demonstrates a 29.69% reduction in RMSE when compared to ANFIS-M4, with a corresponding 29.38% enhancement in MAPE.

Incorporating the Day of Year (DOY) alongside with air temperature into ANN and ANFIS models significantly enhances the prediction of reservoir surface water temperatures. DOY captures seasonal patterns of reservoirs thermal dynamic which influenced by factors such as solar radiation and sunshine duration, enabling models to account for natural fluctuations throughout the year. This temporal variable serves as a proxy for climatic influences, reflecting the time of year and aiding in generalizing predictions across various climatic conditions. Additionally, DOY improves the models' generalization capabilities during cross-validation by introducing the temporal context, complementing meteorological variables like air temperature, and helping models capture long-term trends and cycles that air temperature data alone may not fully capture. Overall, integrating DOY enables ANN and ANFIS models to effectively capture both short-term and long-term variations in reservoir surface water temperature, leading to improved predictive accuracy, especially when applied to unseen data from specific reservoir (Beni Bahdel). Jiang et al. (2022) found DOY to be the dominant factor influencing river water temperature predictions downstream of cascaded dams across diverse machine learning techniques. Similarly, Qiu et al. (2020) revealed that incorporating DOY offered greater predictive improvement compared to adding river flow discharge (Q) alongside air temperature (Tmean).

The performance comparison between ANN and ANFIS models across the eight input combinations revealed no consistent dominance of one approach over the other. In some configurations, ANN models slightly outperformed their corresponding ANFIS counterparts, while in other configurations, ANFIS achieved marginally better results than ANN. Two models were particularly noteworthy: ANN-M2, which uses only Tmean and DOY as inputs, delivered high predictive accuracy while requiring fewer inputs, and ANFIS-M7, which incorporates Tmean, Tmax, Tmin, and DOY, also produced strong predictive accuracy. These results highlight that the selection of the most appropriate modeling mechanism should be guided by the specific application context and the availability of input variables. Moreover, as both ANN and ANFIS are data-driven approaches, their relative performance may differ when applied to datasets from other reservoirs.

In terms of simplicity and parsimony (model requiring fewer inputs), the ANN-M2 model stands out as the most straightforward, efficient, and accurate. It only requires Tmean and DOY as inputs while delivering the best performance among all the models tested.

ANN-M2 and ANFIS-M7 models can also be employed to produce real-time predictions of reservoir surface water temperature (TS) in the northern of Algeria. These predictions rely on air temperature forecasts (Tmean, Tmin, and Tmax) provided by the national weather service, combined with the DOY as input variables.

Accurate surface water temperature predictions using ANN and ANFIS models offer various advantages for lake and reservoir managers, equipping them with the ability to take targeted actions to improve both ecological and operational outcomes. By predicting water temperature fluctuations, managers can enhance water quality monitoring and control, addressing issues related to dissolved oxygen levels, nutrient dynamics, and harmful algal blooms. For example, if predictions suggest increasing water temperatures that may result in oxygen depletion, managers can respond by initiating water circulation systems or aeration measures to preserve sufficient oxygen levels for aquatic organisms. Moreover, these predictions allow for the optimization of water resource allocation by helping managers adjust water withdrawals and releases based on temperature forecasts, balancing the needs of aquatic ecosystems and human consumption. This predictive capability is especially crucial for fish and aquatic life management, where water temperature changes can cause significant stress on sensitive species. With water temperature forecasts in hand, managers can implement preemptive measures like timing water releases or restricting fishing to protect vulnerable populations.

In addition, accurate temperature predictions are critical for controlling algal blooms and eutrophication, two issues that often arise when water temperatures rise. With advance warning, managers can reduce nutrient inflows from agriculture or urban runoff to prevent blooms before conditions worsen. These predictions also contribute to long-term planning and climate change adaptation, helping managers formulate strategies to cope with increasing temperatures. This could include upgrading infrastructure and optimizing reservoir management practices to lessen the impact of extreme temperatures on aquatic ecosystems. Finally, this comprehensive application of temperature forecasts demonstrates their importance in water resource management, from short-term interventions to long-term sustainability planning.

To validate the numerical results (Table 4), Fig. 3 illustrates the observed and predicted surface water temperature (Tw) as time series, and Fig. 4 displays the corresponding scatter plots for the MLR-M1, ANN-M2, and ANFIS-M7 models during the testing phase at the Beni Bahdel reservoir. From both the time series (Fig. 3) and scatter plots (Fig. 4), it is evident that the predictions from the ANN-M2 and ANFIS-M7 models align more closely with the observed Tw compared to the MLR-M1 model.

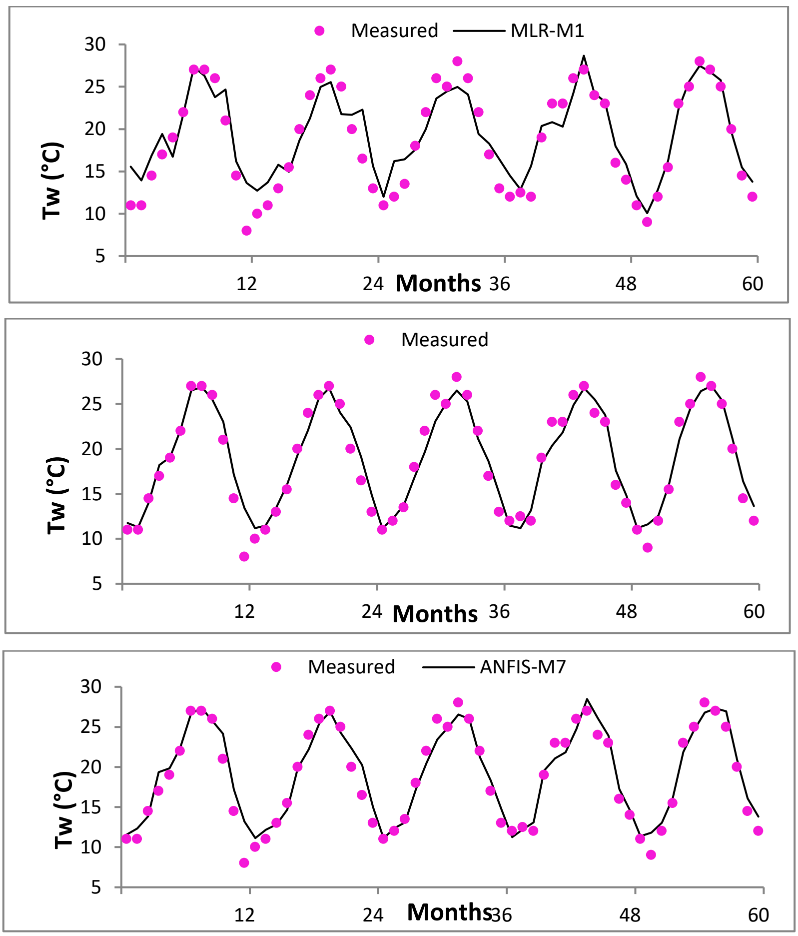
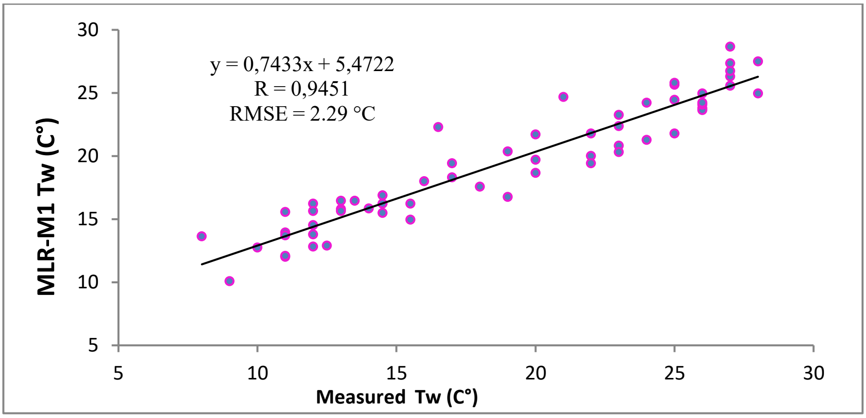
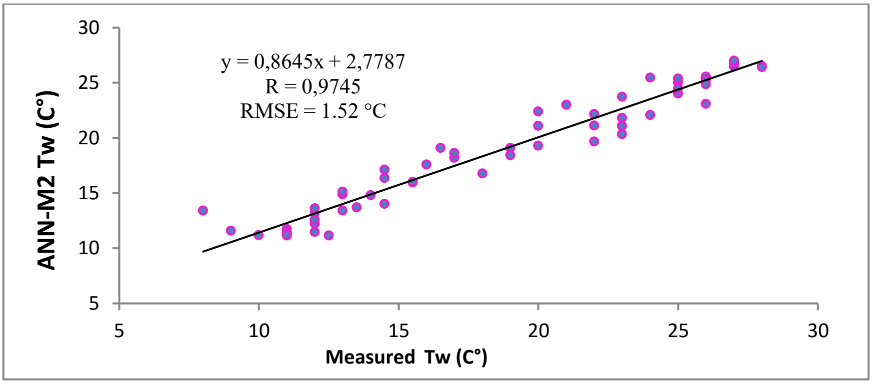


Figure 3: Time series of the observed and predicted water temperature (Tw) in Beni Bahdel reservoir for MLR-M1, ANN-M2 and ANFIS-M7 models





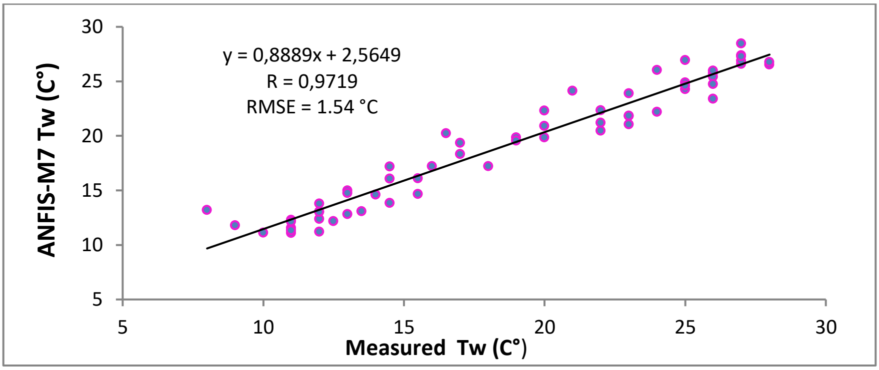


Figure 4: Scatter plots between the observed and predicted water temperature (Tw) in Beni Bahdel reservoir for MLR-M1, ANN-M2 and ANFIS-M7 models

In addition to time series and scatter plots, the performance of all models is assessed using the Taylor diagram (Fig. 5), which combines key metrics such as correlation coefficients (R), standard deviations, and root mean square difference (RMSD) to evaluate accuracy.

This information is presented in a single diagram and compared to observed data (Obs). The closer a model's point is to the red-filled reference point (Obs), the more accurate the model is. The Taylor diagram shows that ANN-M2, with the fewest inputs, yields the highest accuracy, followed by ANFIS-M7 and ANFIS-M2.

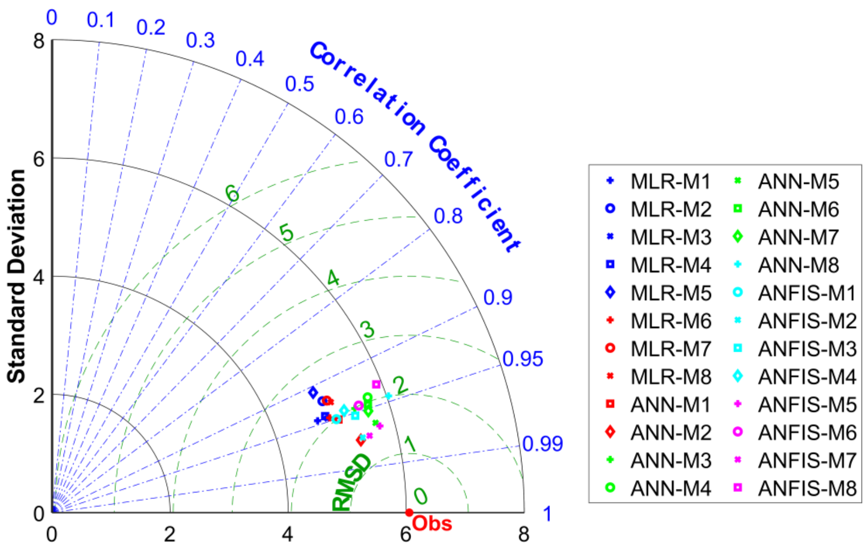


Figure 5: Taylor diagram of all tested models

Sensitivity analysis results

To assess the individual contributions of each input variable to the predicted surface water temperature, a sensitivity analysis was performed on the Artificial Neural Network (ANN) model using 'leave-one-out' method (excluding a specific input each time). The results of this analysis, including the ratios and ranks, are displayed in Table 5.

Table 5: Sensitivity analysis results for ANN models

Models	Ratio	Rank
Without DOY	1.150	1
Without Tmean	0.980	2
Without RH	0.973	3
Without Tmax	0.968	4
Without Tmin	0.940	5

For reservoir surface water temperature, it is evident that the sensitivity analysis of inputs highlights the substantial impact of DOY, followed by mean air temperature (Tmean), relative humidity (RH), maximum air temperature (Tmax) and minimum air temperature (Tmin), respectively.

The sensitivity analysis of reservoir surface water temperature reveals that the day of the year (DOY) has the greatest impact (ratio: 1.150). Since the reservoirs are located in a Mediterranean climate, the seasonal variation in solar radiation, temperature shifts and the length of daylight vary significantly across the year. This makes DOY a crucial factor, reflecting the overall energy input the reservoirs receive over time. Mean air temperature (Tmean, ratio: 0.980) follows, indicating the role of overall atmospheric warmth in heat exchange with the water. Relative humidity (RH ratio: 0.973) also has a substantial effect, highlighting its influence on evaporation and heat retention. Maximum and minimum air temperatures (Tmax; 0.968, Tmin; 0.940) contribute to short-term heating and cooling processes, but are less influential compared to DOY and Tmean.

CONCLUSION

The knowledge of surface water temperature is critical for reservoir management, predicting water quality, and understanding ecological health. In this paper, MLR, ANN, and ANFIS model were evaluated for the estimation of reservoir surface water temperature (Tw) in the northern of Algeria using site based cross-validation approach. The findings of this study lead to the following conclusions:

Both the ANN and ANFIS models outperformed the MLR model across various performance metrics, providing reliable predictions of surface water temperature in the study area. However, the ANN model (M2) stood out for its simplicity, accuracy, parsimony, robustness, stability, and overall effectiveness in predicting water temperature (Tw).

Training the models with combined data from six different reservoirs across Algeria improves their generalization capacity. The inclusion of varied data allows the models to adapt to a broader spectrum of conditions, enhancing their applicability to regions throughout northern Algeria.

The sensitivity analysis results reveal that seasonal variations represented by DOY, have the most significant influence on reservoir surface water temperature. After DOY, the variables Tmean (mean temperature), RH (relative humidity), Tmax (maximum temperature), and Tmin (minimum temperature) exhibit progressively lower levels of impact.

This research underscores the importance of incorporating the DOY as an input variable in surface water temperature prediction for reservoirs, as it can substantially enhance the accuracy of the predictions.

The results of this study offer valuable insights for predicting surface water temperature in reservoirs across northern Algeria. Notably, they highlight the potential of using only mean air temperatures and the day of the year (DOY) as key inputs, simplifying the modeling process while maintaining accuracy.

Accurate temperature predictions provide managers with a vital tool to anticipate and address issues related to water quality, aquatic life health, and ecosystem stability. With this foresight, they can implement timely and effective interventions, improving the overall condition and sustainability of lakes and reservoirs.

While the ANN and ANFIS models need to be tested against other machine learning techniques using large datasets that, alongside air temperature, include variables such as solar radiation, sunshine duration, evaporation, and water inflows and outflows. These machine learning techniques show great potential for unraveling the complex relationships between these inputs and the resulting output (surface water temperature).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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