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Predicting eutrophication dynamics using artificial neural networks

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Abstract: Dal Lake, the freshwater lake in Srinagar, Jammu and Kashmir, has experienced significant water quality changes over the last two decades due to anthropogenic activities, intensifying eutrophication and threatening its ecological integrity. The study aimed to identify the main limiting factors of eutrophication process in Dal Lake and to rate the impact of traditional eutrophication drivers, i.e. total nitrogen (TN), ammonium (NH_4^+), total phosphorus (TP), orthophosphate (PO_4^{3-}), *WT* (water temperature), *T* (transparency), and chemical oxygen demand (*COD*), Artificial neural networks (ANNs) were employed to identify key drivers to develop predictive models of eutrophication dynamics. Three ANN models with different input combinations were developed. In an initial train–test split, the most complex configuration (model 3) yielded the highest correlation with the index of trophic state (*ITS*) (training R^2 = 0.24, testing R^2 = 0.20, r = 0.46–0.49), whereas 5-fold cross-validation showed that the simpler model 2 achieved the lowest average root mean square error (*RMSE*) and mean absolute error (*MAE*) but the highest mean R^2. Overall explanatory power was modest ($R^2 \le 0.20$), indicating that the ANNs captured only a small proportion of *ITS* variability. Permutation-based sensitivity analysis showed that *COD* and TP are consistently the most influential predictors of *ITS*, while the remaining nutrient variables (TN, PO_4^{3-}, NH_4^+) contributed weakly in this dataset. Thus, the ANN approach yields only partially informative insights into the relationships between water-quality variables and *ITS* in Dal Lake and is not yet suitable as a stand-alone forecasting tool for eutrophication dynamics.

Keywords: artificial neural networks (ANNs), Dal Lake, environmental monitoring eutrophication, machine learning, nutrient parameters, prediction, water quality prediction, wastewater reuse

INTRODUCTION

Eutrophication is a major global environmental problem that negatively impacts freshwater, estuarine, and coastal ecosystems. The main drivers of eutrophication are excessive nutrient loads discharged from different sources (Yang *et al.*, 2008). Eutrophication and its consequences have become major global concerns owing to their long-term detrimental effects on water quality and lake ecosystem equilibrium (Homayoun Aria, Asadollahfardi and Heidarzadeh, 2019). Lakes are treasures of the natural environment and play a crucial role in regional water balance, climate conditions, and economic development (Rashid *et al.*, 2017). Geochemical studies over the past five decades have shown that human activities are responsible for the deterioration of lake ecosystems and their catchment areas at an alarming pace by changing the biochemistry and biophysical setup of natural ecosystems (Rather and Dar, 2020b). Adverse impacts on lake ecosystems in the Kashmir region lead to degradation, especially in Dal Lake, which quickly deteriorates in trophic status under extreme anthropogenic stress (Rashid *et al.*, 2017). The primary causes of eutrophication were identified as excessive, such as pollutant loads introduced into the lake and various human activities in the watershed area and its improper development.

This situation requires the immediate development of a lake ecosystem management strategy to protect biological resources and improve water quality. The basic task when elaborating such strategies is the appropriate system of eutrophication monitoring, embracing the regular measurements of eutrophication indicators and the appropriate methodology for trophic status assessment. This provides an opportunity for the formulation of prognostic models of lake eutrophication development under different scenarios. Prediction remains challenging for the following reasons: (1) temporal and spatial differences of geographical, meteorological, hydrological, and biological conditions in different basins of the lake; (2) lack of a regular monitoring system devoted to the eutrophication process; (3) lack of a reliable assessment method adopted to the Dal Lake conditions (Kumar *et al.*, 2022). Classical modelling approaches for eutrophication consist of process-based models (mechanistic or deterministic ecological models that denote the information of nutrient cycling, light penetration, phytoplankton growth, etc.), empirical statistical models, and simple time-series methods. Although process-based models are more beneficial because they gather validated causal mechanisms and require detailed data (related to nutrient dynamics, hydrodynamics, and biological and chemical parameters), they are computationally intensive. These models are easy to calibrate, but there is a weakness in the generalisability across sites (Wang and Wang, 2021).

Water quality issues have been studied by limnologists using multi-dimensional lake and reservoir hydrodynamic and water quality models created with sophisticated computational capabilities and a better understanding of eutrophication processes (Kuo *et al.*, 2007. In contrast to conventional statistically based water quality models, which presume that the response and prediction variables have a linear and normally distributed connection, artificial neural networks (ANNs) can map the nonlinear interactions between variables that are typical of ecosystems (Huo *et al.*, 2013). Previous applications of the ANNs to eutrophication have mainly been focused on the classical indicators, such as chlorophyll a and Secchi depth and on lakes or reservoirs outside the specific context of Dal Lake. Despite the availability of the hydro-chemical data related to the Dal Lake, *ITS*-based modelling of the trophic state, specifically by using the long-term water quality data for Dal Lake, has not been developed yet. Recent studies on lakes, including hydro-chemical assessments such as Kaphle *et al.* (2025) for Syarpu Lake, underline the need for site-specific, data-driven tools to understand eutrophication processes in sensitive lakes.

In most of the lakes, the trophic state is assessed by applying indices based on chlorophyll a, transparency (Secchi depth) and nutrient concentrations. However, for the Dal Lake, there is no availability of long-term and continuous data on chlorophyll a; rather, the data is incomplete. In such a situation, the most optimal methods for assessing the trophic state are integrated trophic indices, based on the established correlations of selected parameters. Therefore, the *ITS* reflecting the biotic balance of the water ecosystem was selected as a trophic state criterion. It is based on the established universal correlation between pH and percentage of dissolved oxygen (DO%), which indirectly reflects the balance of primary production in water and its decomposition. The basic parameters monitored regularly in every routine water monitoring, including the Dal Lake, are pH and dissolved oxygen. The *ITS* can be easily adapted to the Dal Lake conditions, allowing that it complements rather than replaces chlorophyll a or Secchi depth-based indices (Escober and Pythias Espino, 2023; Ali and Neverova Dziopak, 2026). Several static and dynamic models have been established to predict and control the eutrophication process since the late 80s in 20th century, but in recent years, data-driven models based on the neural network approach have been successful in ecological modelling, and the significance of these models is that they can duplicate the non-linear relationships among variables, unlike conventional statistical models that are based on linear relationships (Bhagowati *et al.*, 2022. The present study pursues the following objectives: (1) to assess prior limiting factors of eutrophication in Dal Lake, defining its trophic status expressed by *ITS*, (2) to compare the three alternative ANN input structures for *ITS* prediction, and (3) to evaluate the strength of these models based on the *k*-fold cross-validation under limited data conditions

MATERIALS AND METHODS

CHARACTERISTICS OF THE STUDY AREA

Location and geography

Dal Lake is an urban lake of Kashmir located in the Srinagar city of Jammu and Kashmir; it lies between 4°5' and 34°9' N and 74°49' and 74°53' E at a mean altitude of 1583 m a.m.s.l., as shown in Figure 1 (Kumar *et al.*, 2022). It is the second largest lake in the state of Jammu and Kashmir, with a lake surface area of 22 km^2 and a catchment area of 337 km^2 (Ali, Neverova-Dziopak and Kowalewski, 2025). The lake has a multi-drainage basin with a total water holding capacity of 15.45 mln cubic meters (Mm^3), and the open water is spread over 10.5 km^2 (Kumar *et al.*, 2022). The lake is surrounded by the Zabarwan mountain range on the east and the city of Srinagar on the west and occupies the central position in the Kashmir Valley (Rather and Dar, 2020a). The lake has enormous ecological and socio-economic importance; residents obtain their livelihood from the lake through tourism, fisheries, and agriculture (LWDA, 2020).

Hydrology and lake pollution

Dal Lake is mainly fed by a large perennial inflow channel, Telbal Nallah, which drains the largest sub-catchment area of about 145 km^2 and contributes about 80% of the total inflow to the lake, as well as several small streams, viz., Peshpaw Nallah, Shalimar Nallah, Merakhsha Nallah, Harshi Kul, etc., around the shoreline, besides some contribution from groundwater (Jeelani and Shah, 2006). The other minor inflows include Dara Nallah, Nagbal Nallah, and various small tributaries originating from the direct catchment. The main inflow is the Telbal Nallah channel from the Marsar Lake, which brings most of the supply to the lake. Agricultural activities around the inflow of Dal Lake and anthropogenic interventions contribute significant nutrient loading into the lake, and the direct sewage into the lake is also a problematic issue that causes an increase in the eutrophication level in the lake and results in variability in the water quality. Nallah Amir Khan is the main outlet of the Dal Lake, through which the lake connects to the Anchar Lake and finally to the Jhelum River (Qayoom, 2022). Thus, integrating the water balance with the river and wetlands around the lake is necessary (Kumar *et al.*, 2020). Therefore, the two main outflows are actually regulated channels: Dal Gate and Nallah Amir Khan. The glaciers from the upper belt of Dachigam, which covers an area of approximately 337 km^2, are the main source of surface water for

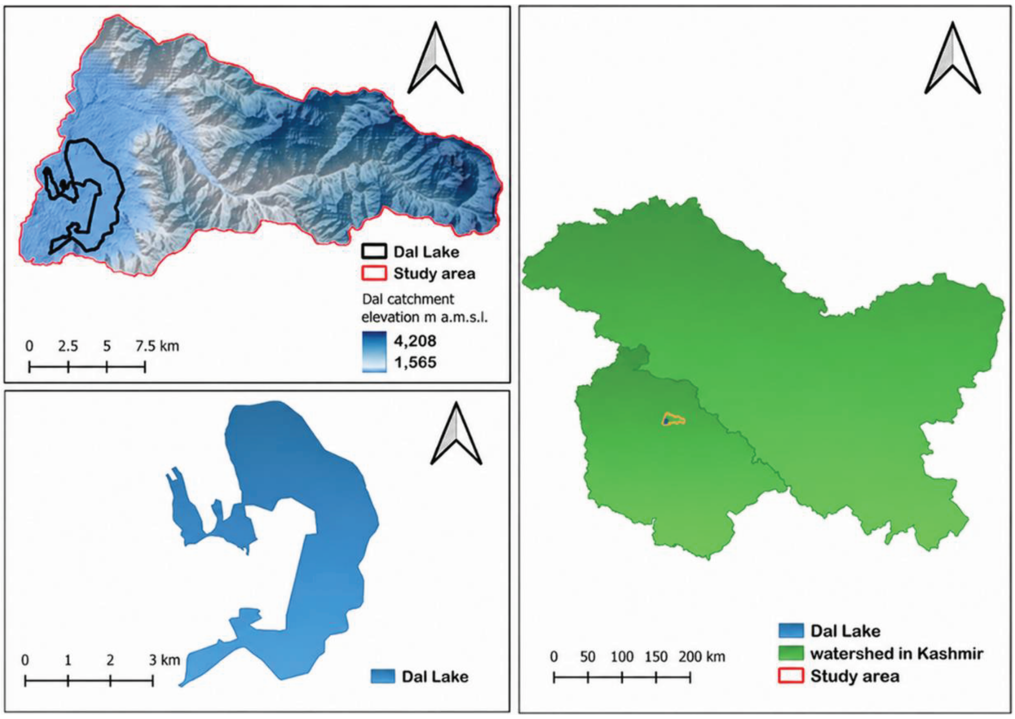

Fig. 1. Location of Dal Lake in the Dal catchment; source: own elaboration

the lake. Additionally, several springs and groundwater sources supply the lake (Ali, Neverova-Dziopak and Kowalewski, 2025). The hydrological system of the Dal Lake and its catchment area is shown in Figure 2, which illustrates the various inflows from the catchment draining into the lake through small tributaries and forming the entire hydrological system.

The Dal Lake is experiencing persistent pollution that leads to eutrophication, a direct impact of anthropogenic activities and watershed degradation (Hassan *et al.*, 2024). Over the three decades, the lake area has been diminished by 11 km^2 due to encroachments and massive silt deposition. The major drivers of the pollution in Dal Lake are untreated sewage, agricultural runoff, and waste from the hundreds of houseboats. In addition, the lake experiences approximately 18 Mg of phosphorus and 25 Mg of nitrogen nutrients annually through major drains from Srinagar city, which leads to the intensification of nutrients concentration (LWDA, 2020). Uncontrolled algal and aquatic weed development has been fuelled by this influx of nutrients, particularly nitrates and phosphates. This is a classic sign of eutrophication, in which the decomposition of algae causes a sudden drop in dissolved oxygen levels, suffocating fish and changing the ecosystem of the lake. Over the last forty years, dissolved oxygen concentration in Dal Lake has drastically decreased, making it unsuitable for native species like the kashir gaad (snow trout, *Schizothorax* spp.), which are now all but extinct in the lake (Sam, 2025). The long-term limnological research revealed that larger amounts of water and sediment chemistry have been altered, also demonstrating the decline in the dissolved oxygen from 7.4 mg·dm^{-3} in 1997 to 6.9 mg·dm^{-3} in 2017, which hurts the aquatic ecosystem, leading to the change in the part of the lake into a hypereutrophic condition (Nazir *et al.*, 2024). The land use and land cover of the Dal Lake and its catchment is shown in Figure 3. The catchment area is classified

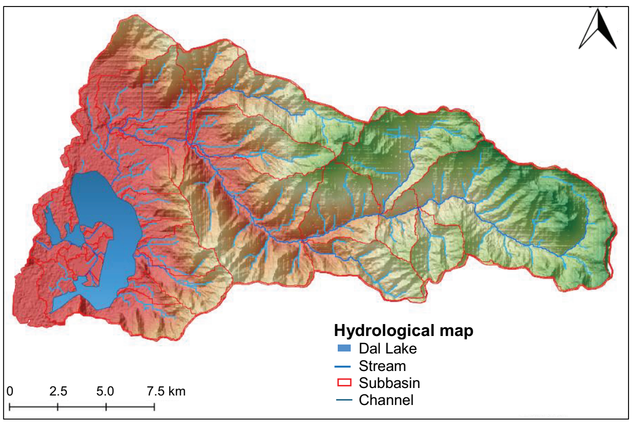

Fig. 2. Hydrological system of Dal Lake and its catchment area; source: own elaboration based on the SWAT model outputs

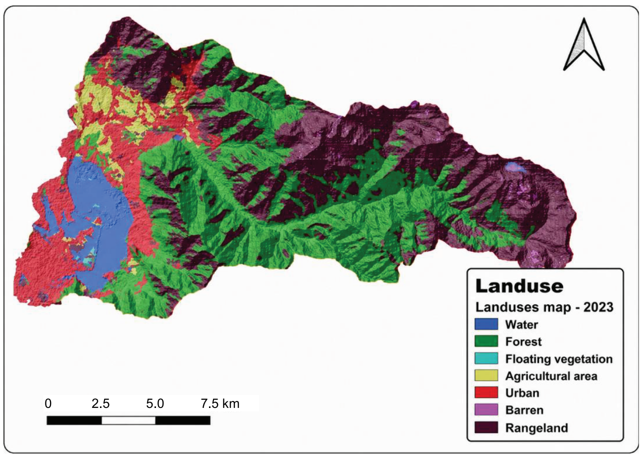

Fig. 3. Land use and land cover in the Dal Lake catchment for 2023; classes, source: own elaboration based on Esri Sentinel-2 10 m Land Use/ Land Cover Time Series data (Land Cover Explorer) and SWAT model outputs

such that the agricultural and urban areas are the main sources of nutrients that contribute to the nutrient load in the lake, with other sources of nutrient load from sewage from the urban area. The map shows the spatial distribution of major classes.

DATA ACQUISITION AND EUTROPHICATION ASSESSMENT

The research study on the Dal Lake ecosystem commenced with the data collection, followed by the organisation and statistical analysis of long-term water quality data (1997–2023). The monthly data corresponding to different seasons were sourced from the Lake Conservation Authority (LCMA), Jammu and Kashmir Pollution Control Board (JKPCB) and the University of Kashmir (KU) for the period from 1997 to 2023. All these organisations conducted systematic monthly sampling at 13 monitoring sites distributed across all four basins, including Hazaratbal, Gagribal, Nigeen and Nishat. These monitoring stations were spatially representative of the lake's hydrological and ecological variability. The dataset included parameters such as pH, chemical oxygen demand (*COD*), total phosphorus (TP), ammonium, (NH_4^+), orthophosphate (PO_4^{3-}), water temperature (*WT*), transparency (*T*), and total nitrogen (TN). The monthly observations were first quality-checked, cleaned and organised into a single full dataset. To ensure temporal consistency and facilitate long-term analysis, monthly values were aggregated into annual means for each parameter, computed for each basin. These basin-wise annual mean values (1997–2023) produced the standardised time series used for the index of trophic state (*ITS*) and artificial neural network (ANN) modelling. Before ANN modelling, the dataset was checked for consistency. The records with missing values were removed, and no interpolation was performed. The outliers within the dataset were observed by using descriptive statistics and the interquartile range (*IQR*) method, and removed to improve the model stability, resulting in 349 observations being used. The cleaned dataset was randomly distributed into training (80%) and testing (20%) subsets to evaluate model performance and robustness. Descriptive statistical analysis was performed to explore the long-term variability and detect annual trend analyses over 26-year periods, with specific emphasis on identifying significant temporal shifts and potential eutrophication patterns in the lake ecosystem. The derived trends serve as a fundamental basis for interpreting the drivers of eutrophication. The overall seasonal variations of the various water quality parameters in Dal Lake are shown in the Figure 4.

All such analyses were carried out to understand the basis of drivers of the eutrophication in Dal Lake and to analyse the prior factors that are responsible for the eutrophication in Dal Lake. The analysis of drivers of eutrophication in Dal Lake aims to identify and understand the primary factors contributing to this ecological issue. Eutrophication, characterised by excessive nutrient enrichment in water bodies, can lead to algal blooms, oxygen depletion, and overall degradation of water quality. By examining various

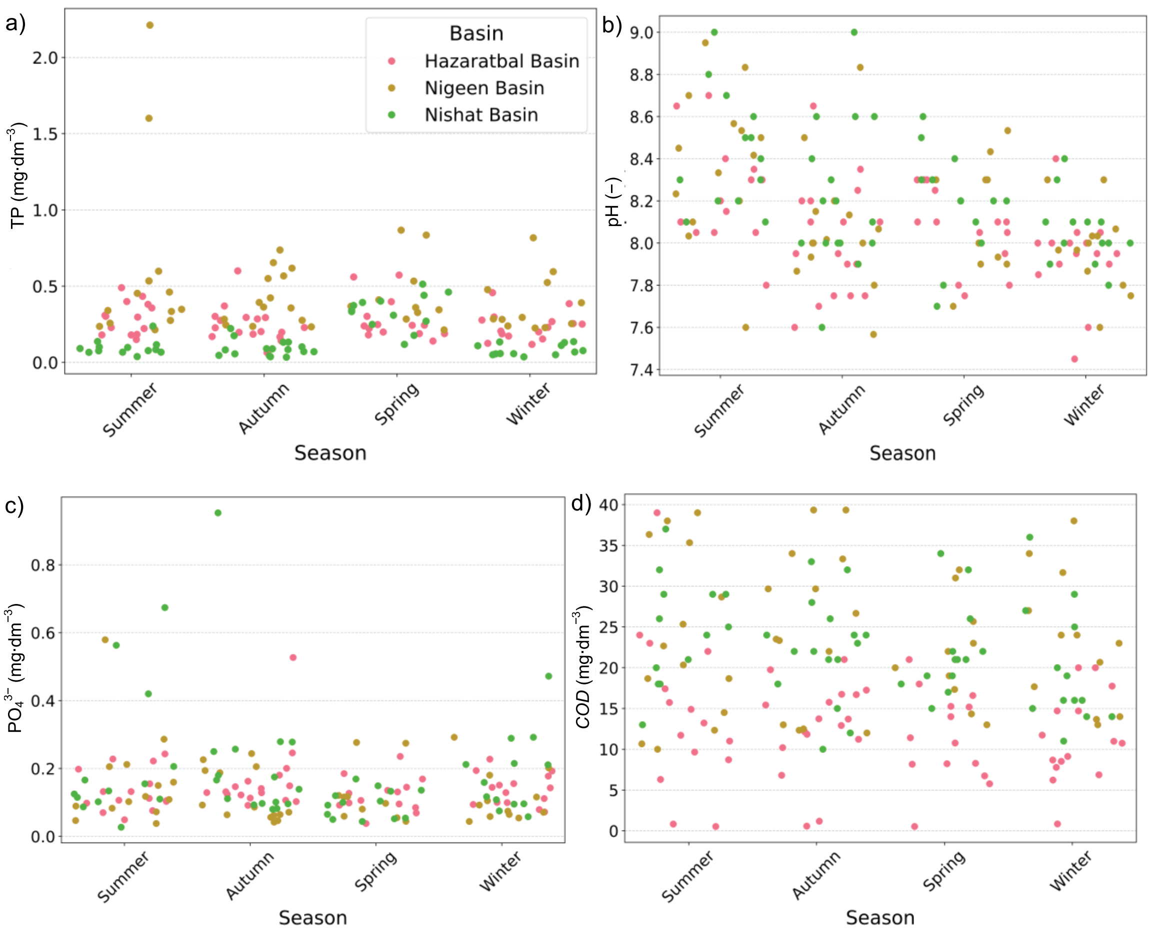

Fig. 4. Seasonal distribution of key water-quality parameters by basin (1997–2023): a) total phosphorus (TP), b) pH, c) orthophosphate (PO_4^{3-}), d) chemical oxygen demand (*COD*); source: own study

potential causes, researchers can pinpoint the most significant contributors to the lake's eutrophication process. These analyses likely involve studying multiple aspects of the lake ecosystem and its surrounding environment. Factors under investigation may include nutrient inputs from agricultural runoff, sewage discharge, atmospheric deposition, and internal nutrient loading from sediments. Additionally, researchers might examine changes in land use patterns, climate variables, and hydrological conditions that could influence nutrient dynamics in the lake.

Eutrophication assessment commonly involves the use of the aggregated indicators such as the Carlson trophic state index (*TSI*) and the Vollenweider trophic index (*TRIX*), as well as the framework implemented by the EU Water Framework Directive (Directive, 2000) and HELCOM. The trophic state evaluation of the water bodies is crucial because of the ecosystem's biotic balance and overall ecological condition. Even though there is availability of numerous classification systems and quantitative indicators, the interpretation of the trophic state remains challenging. The efficient indicators should have the ability to capture the anthropogenic impacts on the aquatic ecosystems, be flexible with data that is efficient enough to easily interpret the impacts that are based on cost-effective and suitable for predictive applications. The *ITS* was used to assess the trophic state of Dal Lake reflects its biotic balance through a calculated index, with the boundary values (Tab. 1). The *ITS* was calculated based on the established correlation between two variables: pH and DO%, which allowed us to easily adopt this index for the Dal Lake conditions (for this relationship high Pearson r value was obtained as 0.97, justifying the choice of *ITS* as a criterion for trophic status for research purposes. The slope coefficient a was obtained from the linear regression of pH versus DO% using the full dataset for Dal Lake. This index was calculated separately for each basin corresponding to each year from the annual mean dataset. The *ITS* is calculated acc. to Equation (1).

Table 1. Index of trophic state (*ITS*) boundary values for different water trophic state

Trophic type of water	*ITS* value
Dystrophic	<5.7–6.0
Ultraoligotrophic	6.0–6.6
Oligotrophic	6.7–7.3
Mesotrophic	7.4–8.0
Eutrophic	8.0–8.5
Hypereutrophic	≥8.6

Source: Ali, Neverova-Dziopak and Kowalewski (2025).

$$ITS = \frac{\sum \mathrm{pH}}{n} + a\left(100 \frac{\sum \mathrm{DO\%}}{n}\right) \tag{1}$$

where: pH = potential of hydrogen, DO% = water saturation with oxygen, a = slope coefficient of pH–DO% linear regression, n = number of measurements.

The dynamics of the trophic state of the Dal Lake, assessed using the *ITS* for the period from 1997 to 2023, is shown in Figure 5. The boundary values of *ITS* for different trophic states are presented in Table 1 (Ali, Neverova-Dziopak and Kowalewski, 2025).

As the results of the *ITS* assessment demonstrate, over the past 25 years, the trophic status of the Dal Lake has oscillated within the hypereutrophic to eutrophic range, with *ITS* values decreasing slightly from 2019 to 2020. This drift in the *ITS* status was related to the government's remediation plans, which resulted in some positive changes in the trophic state. The basin-specific *ITS* values were also calculated to examine spatial differences in the Dal Lake (Fig. 5). However, because the annual sample size per basin is limited, the ANN models in this study were used based on the pooled lake-wide *ITS* series. In the separate basins, slight differences in the eutrophication development can be observed. To understand the causes and regularities of such process development, it is necessary to define the main drivers of these changes. Artificial neural networks (ANNs) are well-suited for predicting eutrophication in Dal Lake because they can model complex, nonlinear relationships among multiple environmental variables, such as nutrient concentrations, temperature, dissolved oxygen, and chlorophyll a The ANNs were applied in this study to understand the influence of each water quality parameter on eutrophication in Dal Lake by developing models that allow us to assess the contribution of each variable as input to the target.

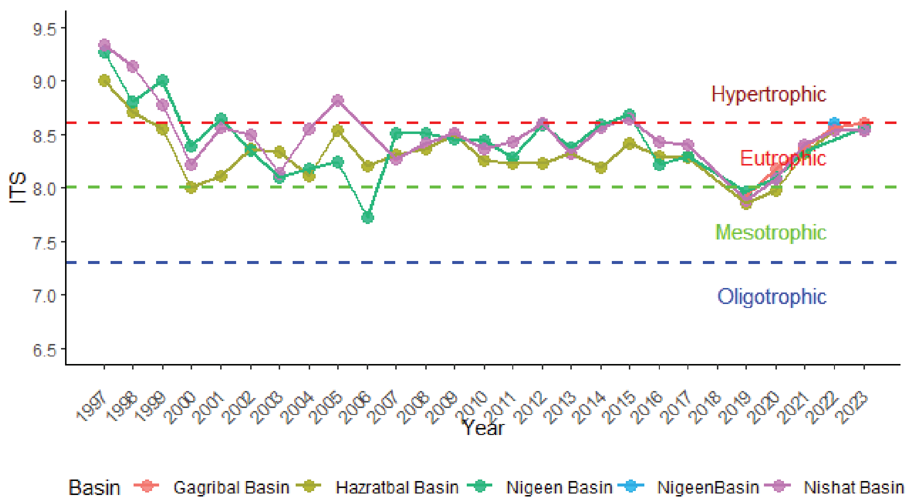

Fig. 5. Trophic state assessment of Dal Lake based on index of trophic state (*ITS*) for the period 1997–2023; source: own study

MODEL APPROACH

There is limited research on Dal Lake eutrophication, with limited data availability on eutrophication indicators, as modelling Dal Lake is quite complicated due to water dynamics, hydrology, and weather conditions. Given the number of complicating factors, such as variability in weather and hydrological conditions of the lake, water-level changes, excessive catchment development (urbanisation, agricultural intensification, and encroachments), and limited high-frequency inflow data, artificial neural networks (ANNs) may be well-suited to simulate scenarios and predict eutrophication in Dal Lake.

Dissolved oxygen (*DO*), total phosphorus (TP), chlorophyll a, and Secchi depth (SD) are commonly used as eutrophication indicators to determine the eutrophication status of lakes. To analyse the nonlinear relationships between these indicators and the trophic level indicators, an ANN model based on back-propagation training was used. In this model, the input nodes represent the historical water quality parameters (1997–2023) that represent the environmental forcing functions to control the lake biochemical processes, while the output nodes correspond to the eutrophication index, and the input and output layers are connected via hidden layers that are responsible for capturing the complex interactions. The backpropagation algorithm is applied to an ANN model to create the relationship between the input and output.

ARTIFICIAL NEURAL NETWORK MODELLING FRAMEWORK

Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are a paradigm for information processing that is inspired by biological nerve systems. The paradigm's innovative structure is a crucial component. It comprises several intricately linked processing neurons that cooperate to address certain issues. Backpropagation neural networks, or ANNs, were used in this investigation (Huo *et al*., 2013). Initially, for the model-3, inputs were taken from total phosphorus (TP), total nitrogen (TN), orthophosphate (PO_4^{3-}), ammonium nitrate (NH_4), chemical oxygen demand (*COD*), season, and water temperature (*WT*). Still, preliminary results revealed that the presence of *WT* in model-3 decreased R^2 and did not improve the *RMSE*. Therefore, *WT* was removed from the final model -3 to avoid redundant or noisy information.

Backpropagation neural networks

Backpropagation was applied as the supervised learning algorithm to iteratively update network weights and minimise the mean-squared error (*MSE*) between the predicted and observed *ITS* values. The MLP Regressor (Multi-Layer Perceptron) class from the scikit-learn library (Python) was used for the implementation of all ANN models. The MLP Regressor is a feed-forward artificial neural network that approximates a non-linear function between input variables and a continuous target by stacking an input layer, one or more hidden layers, and an output neuron. The model learns the mapping by iteratively adjusting connection weights with backpropagation to reduce the *MSE* between predicted and observed *ITS* values. Backpropagation training was performed with a single hidden layer of 12 neurons, and a logistic (sigmoid) activation function was used in the hidden layer (activation = logistic). The adaptive moment estimation (Adam) optimiser was employed for weight updating, with an initial learning rate of 0.2 and an adaptive learning rate schedule. The 2500th iteration was used to train each model, with L2 regularisation (alpha = 0.001) to limit overfitting, and a fixed random seed (random state = 42) was applied to ensure reproducibility.

MODEL DESCRIPTION

Parameters of an artificial neural network

In the backpropagation ANN, the number of key parameters is required. Initially, the number of input units must be selected. In the present study, three models were built to predict the prior limiting factors that influence the *ITS* values in Dal Lake, and therefore the trophic state of this water body. The seven water quality parameters, recognised as the basic indicators of eutrophication were chosen: TN ($mg \cdot dm^{-3}$), TP ($mg \cdot dm^{-3}$), NH_4^+ ($mg \cdot dm^{-3}$), PO_4^{3-} ($mg \cdot dm^{-3}$), *COD* ($mg \cdot dm^{-3}$), *WT* (°C) and *T* (m), and among these parameters, three models were developed based on correlation with the *ITS*, as shown in the Figure 6.

The total phosphorus is an important indicator for eutrophication in Dal Lake, and total nitrogen is also another important indicator for eutrophication. Other elemental forms of nitrogen and phosphorus also play a role in eutrophication. Eutrophication within the lake is also influenced by changes in temperature and *COD*, and temperature variability impacts eutrophication by promoting algal growth and depletion of dissolved oxygen (*DO*) availability in the lake. Also, higher *COD* levels in the lake indicate organic pollution that depletes oxygen and elevates eutrophication by nutrient release. Hence, all the parameters play an important role in the eutrophication of lakes. Finally, three models were built to predict the influence of these indicators on *ITS*. The back propagation (BP) structures, which interconnect the input and output layers via hidden layers that consist of several neurons, are shown in Figure 7.

Parameters of testing and training

Three prediction models were built for *ITS* to analyse the most influential eutrophication indicator for *ITS* in Dal Lake. Research has found that the causes and effects of eutrophication, and possible mitigation strategies for lakes and impoundments, are complex and are frequently examined using several types of models (Kuo *et al*., 2007. The field data were randomly divided into training and test sets. The training set included 75% of the field data, and the testing set consisted of the remaining 25%. Three models were established for *ITS*. Model-1 for *ITS* was built by taking the inputs of *T* (m), *WT* (°C), and TN ($mg \cdot dm^{-3}$). The inputs for the model-2 for *ITS* were TP ($mg \cdot dm^{-3}$), PO_4^{3-} ($mg \cdot dm^{-3}$), NH_4^+ ($mg \cdot dm^{-3}$), and *COD* ($mg \cdot dm^{-3}$), and model-3, where all the parameters were taken except (*WT*) to avoid adding redundant or noisy information as the inputs for the model-3, were *T*, TN ($mg \cdot dm^{-3}$), PO_4^{3-} ($mg \cdot dm^{-3}$), NH_4^+ ($mg \cdot dm^{-3}$), *COD* ($mg \cdot dm^{-3}$), and season. The parameters are listed in Table 2. Network weights and biases were initialised randomly in the range −0.1 to 0.1 using a fixed random number seed to allow the experiment to be reproduced. This range was chosen for all models, where they could be easily run. In this study, all BP neural network models consist of three interconnected layers,

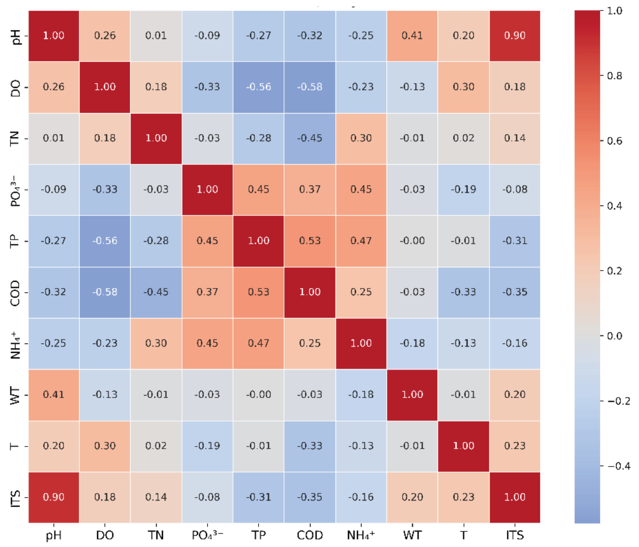

Fig. 6. Correlation matrix of water quality parameters and index of trophic state (*ITS*) in Dal Lake; *DO* = dissolved oxygen, TN = total nitrogen, PO_4^{3-} = orthophosphate, TP = total phosphorus, *COD* = chemical oxygen demand, NH_4^+ = ammonium, *WT* = water temperature, *T* = transparency, TP = total phosphorus; source: own study

Table 2. Neural network parameters (number of samples = 349, activation function – sigmoid, learning rate – 0.2, momentum = 0.9, training iteration = 2,500, and used software – Python 3.x, Scikit-learn)

Model	Input variables	Network architecture
Model-1	*T*, *WT*, TN	3-layer input – 3 output – 1 hidden – 12
Model-2	TP, PO_4^{3-}, NH_4^+, *COD*	3-layer input – 4 output – 1 hidden – 12
Model-3	TP, TN, PO_4^{3-}, NH_4^+, *T*, *COD*, season	3-layer input – 8 output – 1 hidden – 12

Explanations: *T*, *WT*, TN, TP, PO_4^{3-}, NH_4^+, *COD* as in Fig. 6.
Source: own elaboration.

with hidden layers containing nodes. The learning rate should be selected with flexibility in order to expedite the training and convergence of the weight values. In this study, the initial learning rate was set to 0.2 to balance convergence speed and numerical stability, acknowledging the weights to be updated fast and help the optimisation process avoid shallow local minima, thereby enhancing the efficiency of backpropagation. All three models differ from each other, from the simplest structure in *ITS* with three and four inputs to the most complex structure with five input units.

Performance assessment of artificial neural network models

The performance of the ANN models on the single train-test split was assessed by using root-mean square error (*RMSE*) and Pearson correlation (*r*) between the observed and predicted *ITS*. The *RMSE* measures the average size of the prediction error in *ITS* units, so smaller values represent more accurate predictions.

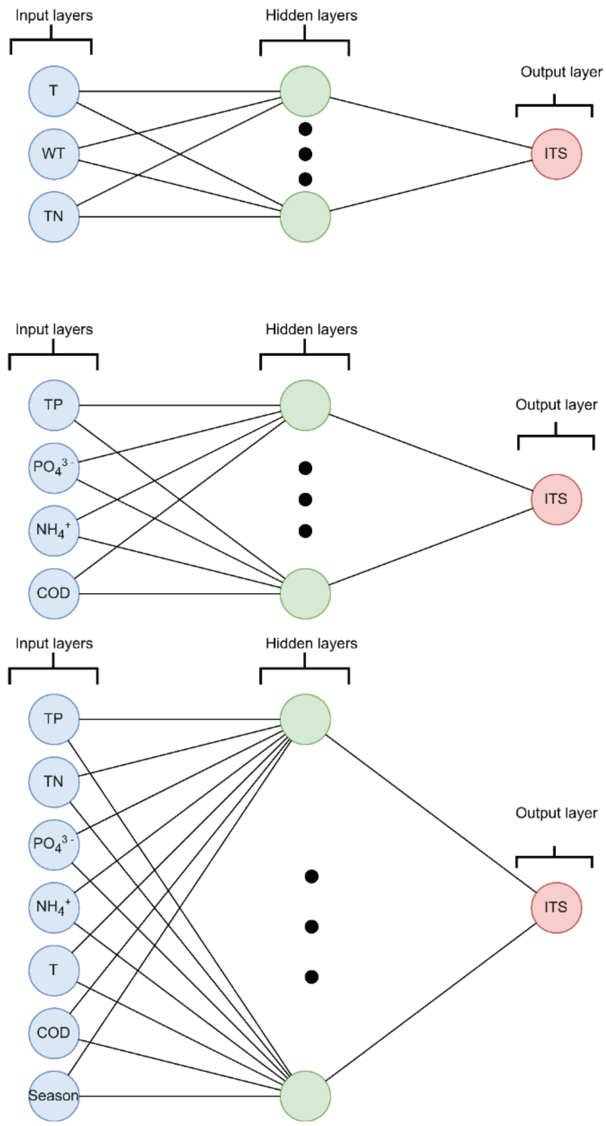

Fig. 7. Artificial neural network (ANN) structures of index of trophic state (*ITS*) models for Dal Lake; *T*, *WT*, TN, TP, PO_4^{3-}, NH_4^+, *COD* as in Fig. 6; source: own elaboration

The Pearson correlation signifies how well the models show the pattern of variations in *ITS*; the higher the value, represents a stronger the linear relationship. Three models achieve almost the same values (0.27–0.30), indicating model-3 captures the *ITS* pattern somehow better on this specific train-test split (Tab. 3).

RESULTS

RESULTS OBTAINED USING MODEL-1

Three models were established to analyse the most influential factors for the index of trophic state (*ITS*) for Dal Lake. The water quality parameters were grouped based on their correlation strength with the *ITS*. The results of the backpropagation neural network for model-1 training and testing are shown Figure 8. The root mean square index (*RMSE*) values for training and testing are 0.30 and 0.28, and the correlations are 0.33 and 0.33, respectively. The model is developed to predict the most influential factors for the *ITS*.

Table 3. Performance of artificial neural network (ANN) models based on single train–test split results for index of trophic state (*ITS*) prediction

Set	Root mean square error (*RMSE*)			Pearson correlation (*r*)		
	model-1	model-2	model-3	model-1	model-2	model-3
Training	0.30	0.30	0.27	0.33	0.30	0.48
Testing	0.28	0.28	0.27	0.33	0.39	0.48

Source: own study.

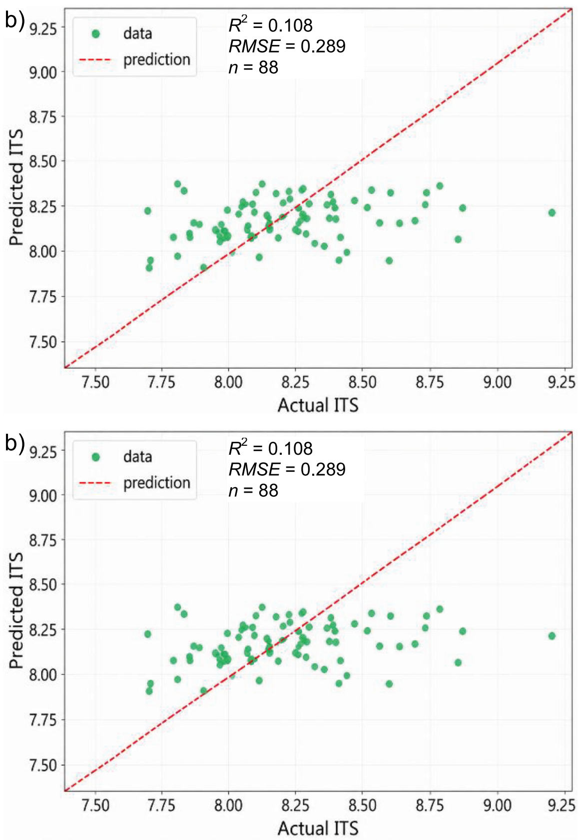

Fig. 8. Actual vs predicted index of trophic state (*ITS*) values for model-1: a) training dataset, b) testing dataset; R^2 = determination coefficient, *RMSE* = root mean square error, *n* = number of samples; source: own study

The scatterplots of observed vs predicted *ITS* values for model-1 explain that the ANN prediction cluster within a narrow range and does not obtain the full variability of the observed *ITS* values. The correlation between training and testing is low (r = 0.33), corresponding to an R^2 of about 0.11, indicating that model-1 explains only a smaller fraction of the *ITS* variability. The entire eutrophication dynamic is a complex process that depends on other biological and chemical parameters that may require improving the prediction performance of *ITS*.

RESULTS FROM MODEL-2

In model-2, TP (mg·dm^{-3}), NH_4^+ (mg·dm^{-3}), PO_4^{3-} (mg·dm^{-3}), and *COD* (mg·dm^{-3}) were used as input parameters in the ANN model, which was used as a predictor of *ITS* and showed weak predictive performance with the training (R^2 = 0.079) and testing (R^2 = 0.109), as shown in Figure 9, respectively. The predictive errors of testing and training (*RMSE* = 0.289–0.307, *MAE* = 0.22–2.24) were relatively small, and the predicted and observed plots demonstrated a narrow range of predicted *ITS* values, indicating limited capability to reproduce the full variability of the observation.

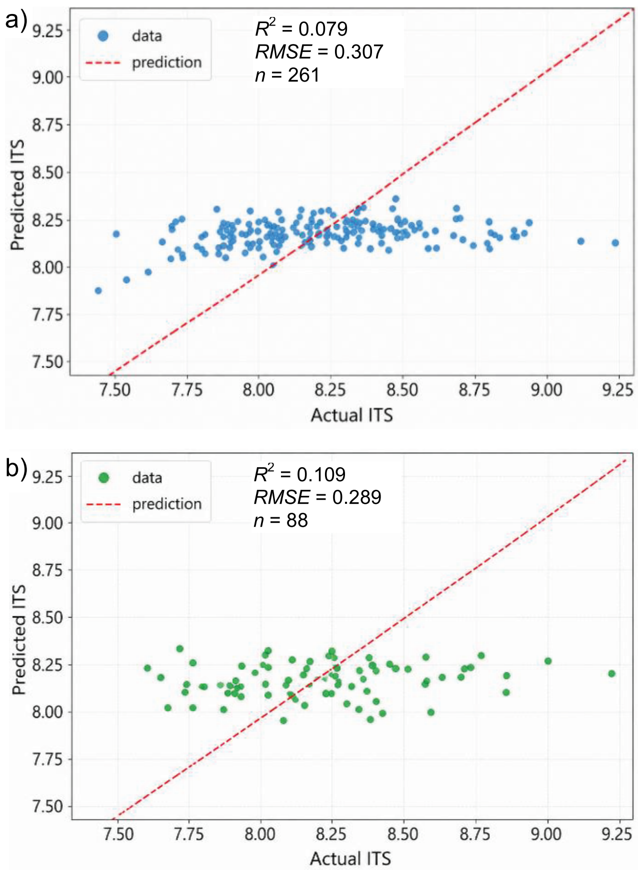

Fig. 9. Actual vs predicted index of trophic state (*ITS*) values for model-2: a) training dataset, b) testing dataset; R^2, *RMSE*, and *n* as in Fig. 8; source: own study

However, the testing correlation (0.39) was slightly higher than that of model-1 (r = 0.33), indicating that, in comparison to transparency, water temperature, and total nitrogen, nutritional and organic load characteristics had a somewhat greater but still small impact on *ITS*.

RESULTS FROM MODEL-3

In model-3, the introduction of a wider set of water quality parameters TP (mg·dm^{-3}), TN (mg·dm^{-3}), PO_4^{3-} (mg·dm^{-3}), NH_4^+ (mg·dm^{-3}), *T* (m) and season showed the best performance among the tested models. The training and testing results showed similar performance (R^2 = 0.241 and R^2 = 0.198), with *RMSE*s of 0.279 and 0.274, and *MAE*s of 0.207 and 0.202, respectively. This indicates consistent but moderate predictive errors, as shown in Figure 10.

In the final train-test split, model-3 obtained an R^2 of about 0.20. This shows that model-3 indicates slightly more *ITS* variability than the other two models, but still leaves a gap in the variability explained.

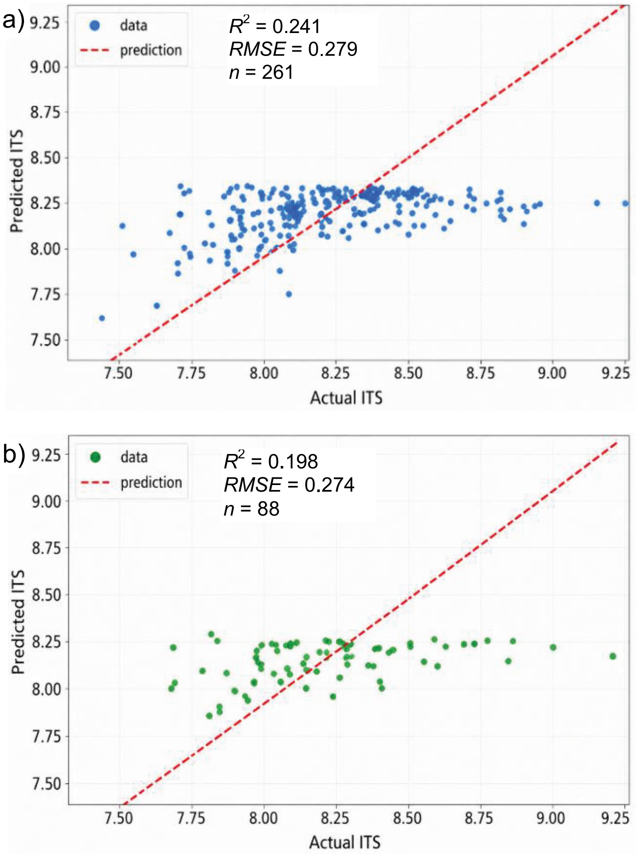

Fig. 10. Actual vs predicted *ITS* values for model-3: a) training dataset, b) testing dataset; source: own study

The comparative analysis of three ANN models highlights the improvement in the predictive performance with the involvement of the diverse input variables, as in the case of model-1, which was based on physical parameters (transparency, water temperature, and TN), and showed the weak predictive ability (R^2 = 0.11, r = 0.33), indicating their lesser role in describing the *ITS* variability (Tab. 4). Model-2, which used the nutrient and organic load indicators (TP, PO_4^{3-}, NH_4^+, *COD*), revealed slightly higher correlations (r = 0.39) that indicate that the trophic state is more influenced by the nutrient dynamics than by physical conditions separately. The model-3, which is the integration of nutrient, organic matter, and physical parameters (TP, TN, PO_4^{3-}, NH_4^+, *COD*, *T* and season), obtained the highest fit in a single train-test split (training R^2 = 0.24, testing R^2 = 0.20, r = 0.46–0.49, however still describes only 20% of the variance in *ITS*. All the outcomes from each model highlight that nutrient enrichment, organic load and seasonal dynamics put a stronger influence on the trophic state of the Dal Lake than the physical parameters alone, while the overall explanatory power of the current ANN models remains modest.

SENSITIVITY ANALYSIS (PERMUTATION IMPORTANCE)

To evaluate the influence of each input variable on the ANN models, the sensitivity analysis is the most commonly used method, which was used on the relatively complicated network (Huo *et al.*, 2013). Permutation importance was used to quantify the contribution of each input variable to the *ITS* prediction error for each ANN models. The analysis was applied to the same dataset used for the model training and testing (349 observations, by randomly permuting one predictor at a time, recomputing the model error (*RMSE*), and recording the increase in error. This procedure was repeated 100 times per variable, and the mean increase in *RMSE* was taken as the permutation importance score, with higher values showing a stronger influence on model performance. The parameter importance score for each input variable in predicting the *ITS* for model-1, model-2, and model-3 is explained in the plots (Fig. 11). The high-importance parameters with high scores feature indicate that the random permuted, cause a larger decrease in the model's performance, suggesting that their influence is more on the model's predictions. The box plots illustrate the distribution of the importance of different parameters across multiple permutations (Fig. 11).

Across the three models, *COD* and TP have the highest permutation importance, specifically in model-2 and model-3, whereas WT is influential in model-1. However, in model-3, T, TN, PO_4^{3-}, and season show non-negligible effects, indicating additional, although weaker, information for predicting *ITS*, as shown in Figure 12.

The parameter contribution matrix (Fig. 12) confirms that *COD* and TP have the highest mean permutation importance across the three models, specifically higher effects in model-2 and

Table 4. Comparative performance of artificial neural network (ANN) models for predicting the index of trophic state (*ITS*)

Model	Input variables	Training R^2	Testing R^2	Training correlation (r)	Testing correlation (r)	Key observation
1	*T*, *WT*, TN	0.109	0.108	0.332	0.337	physical parameters alone give weak predictive power; they explain only a small part of *ITS* variability physical (*T*, *WT*) and chemical (TN) parameters together give weak predictive power and account for only a small fraction of *ITS* variability
2	TP, PO_4^{3-}, NH_4^+	0.079	0.109	0.30	0.39	nutrient and organic-matter indicators slightly improve prediction compared with model-1
3	total TP, TN, PO_4^{3-}, NH_4^+, *COD*, *T*, season	0.241	0.198	0.49	0.46	highest fit in the single train-test split; combining nutrients, organic load and seasonal/physical factors yields the strongest association with *ITS*, but still explains only about 20% of its variability

Explanations: *T*, *WT*, TN, TP, PO_4^{3-}, NH_4^+, *COD* as in Fig. 6.
Source: own study.

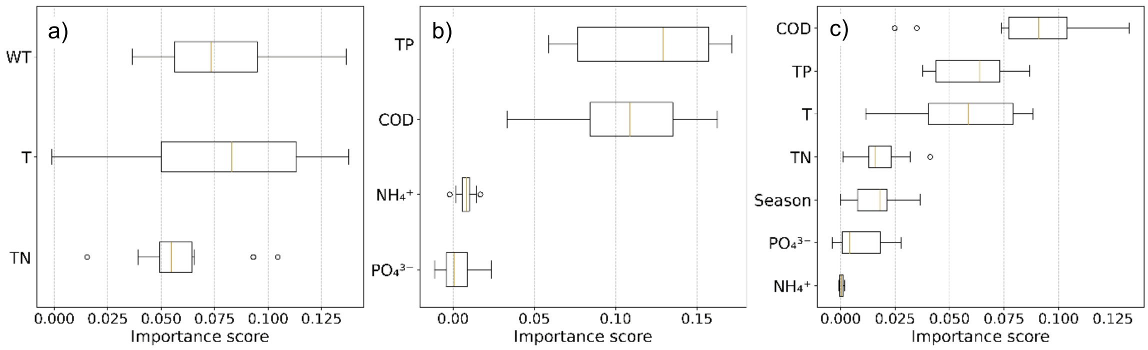

Fig. 11. Permutation importance of three models: a) model-1, b) model-2, c) model-3; *T*, *WT*, TN, TP, PO_4^{3-}, NH_4^+, *COD* as in Fig. 6; source; own study

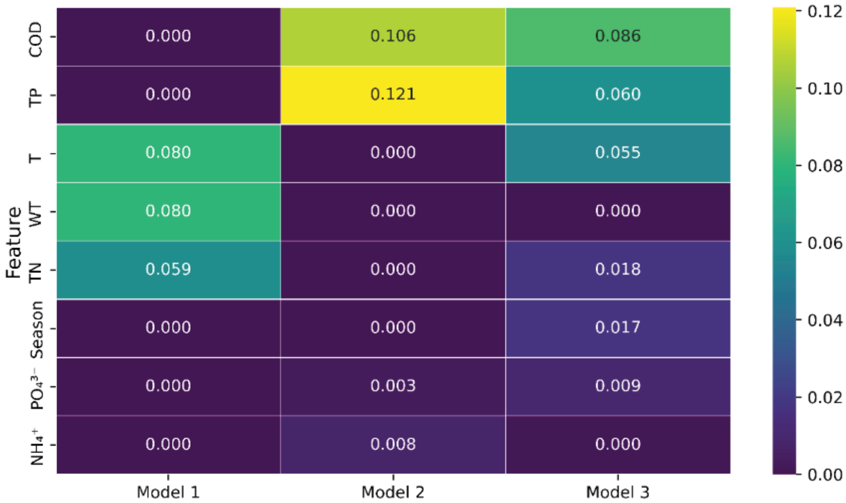

Fig. 12. Parameter contribution matrix based on mean permutation importance for index of trophic state (*ITS*) prediction; *COD*, TP, *T*, *WT*, TN, PO_4^{3-}, NH_4^+ as in Fig. 6; source; own study

model-3. For model 1, the physical parameters *T* and *WT*, together with the chemical parameter TN, exhibit clear permutation importance, suggesting that these variables play a meaningful role in explaining *ITS* variability.

Slightly negative importance values explain that permuting a parameter can sometimes decrease the prediction error instead of increasing it, which indicates that this predictor does not provide stable, specific information for *ITS* and acts basically as noise. These small or negative values are likely affected by sampling variability, collinearity among the input variables and the modest size of the dataset, and they indicate that few predictors are weak or redundant, rather than that the ANN models are strongly over-parameterised.

K-FOLD CROSS-VALIDATION

In this study, *k*-fold cross-validation was applied to evaluate the ANN model and quantify its predictive performance. As in previous research, it was seen that under a small data size, results might show poor performance in ANN models, so under these situations, the *k*-fold cross-validation is considered a good option (Hadjisolomou *et al.*, 2021). This approach prevents overfitting, ensures stability, provides an objective estimate of prediction performance, especially when the data size is small and variability is high, such as in complex lake or reservoir systems (Deng, Chau and Duan, 2021). The studies on eutrophication prediction using ANN models revealed that the *k*-fold cross-validation gives stronger generalisation and robust outcomes as compared to the simple train-test split (Latif *et al.*, 2022). The results of the *k*-fold cross-validation for the three ANN models used in eutrophication prediction, provide an average summary of *k*-fold cross-validation, and present the combined assessment across four key performance metrics: *RMSE*, *MAE*, and R^2 prediction are illustrated in Figure 13 and Table 5.

It should be noted that the higher R^2 and correlation values obtained for model-3 in a single train-test split (training R^2 = 0.197, testing R^2 = 0.195) represent a single random partition of the data, whereas the *k*-fold cross-validation results in Table 5 represent average over multiple folds and therefore provide a more conservative estimate of out-of-sample performance. Because the dataset is relatively small and extremely variable, different splits can lead to optimistic outcomes for one specific train-test subset, while *k*-fold cross-validation tends to lower this optimism and may even produce near-zero or slightly negative average R^2 when the true explanatory power of the model is low.

The lower values of the *RMSE* and *MAE* indicate better model accuracy and reliability. The model-2 shows the lowest average *RMSE* (0.297) and *MAE* (0.223), whereas model-1 and model-3 have slightly higher average errors (*RMSE* = 0.30–0.31, *MAE* = 0.228). In terms of the R^2, which represents the fraction of *ITS* variability described by the models, model-2 obtained the

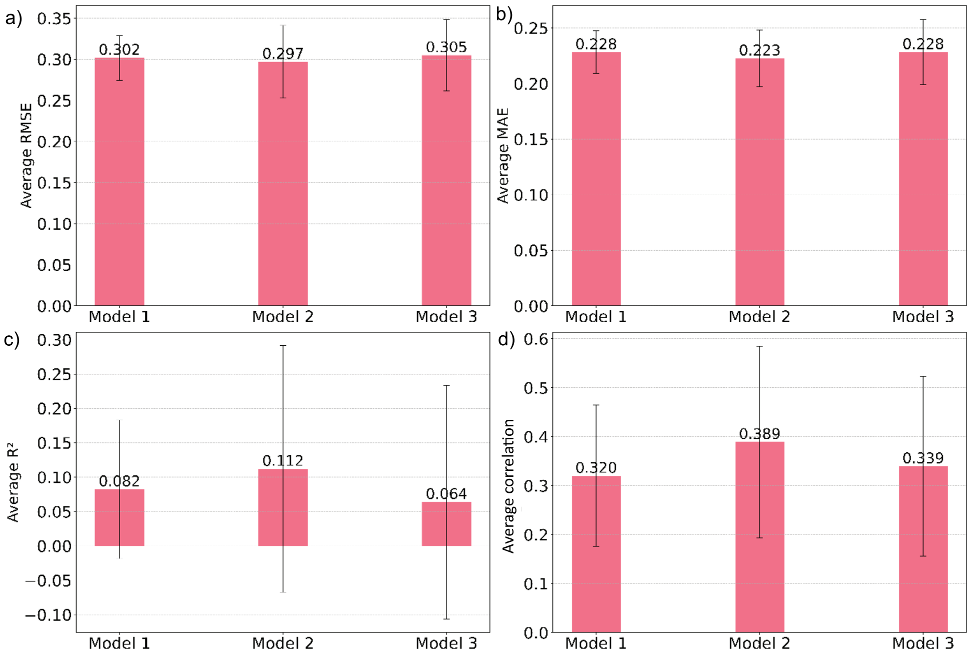

Fig. 13. Average values ±standard deviations of: a) root mean square error (*RMSE*), b) mean absolute error (*MAE*), c) determination coefficient (R^2), d) correlation over 5-fold cross-validation for models 1–3; source: own study

Table 5. Summary of 5-fold cross-validation results (mean ±standard deviation of test metrics across folds)

Model	*RMSE*		*MAE*		R^2		Corr	
	mean	*SD*	mean	*SD*	mean	*SD*	mean	*SD*
1	0.302	0.027	0.228	0.019	0.082	0.101	0.320	0.144
2	0.297	0.044	0.223	0.026	0.112	0.179	0.389	0.195
3	0.305	0.043	0.228	0.029	0.064	0.170	0.339	0.184

Explanations: *RMSE* = root mean square error, *MAE* = mean absolute error, R^2 = determination coefficient, Corr = correlation.
Source: own study.

maximum mean value (0.112), followed by model-1 (0.082) and model-3 (0.064), confirming that all the models explain only a small proportion of the *ITS* variability. The correlations between the observed and predicted *ITS* come out moderate for all models (0.320, 0.389 and 0.339 for models 1–3, respectively), as model-2 again presents slightly better on average. The variability in the error bars in each panel can be seen across folds, signifying the consistency of each metric forecasting in environmental studies. The *k*-fold cross-validation outcomes show that model-2 provides the most favourable balance error and explained variance, whereas model-3 achieved the better performance in the initial single train-test split; its evident advantage does not generalise consistently across the different data splits. The current small and variable dataset, we consider the *k*-fold cross-validation metric to be more reliable than a single random split, so we prioritise the cross-validation performance when comparing models.

DISCUSSION

The study highlights the possibility of using the potential of artificial neural networks (ANN) for predicting the prior factors that have the greatest impact on the trophic state of Dal Lake, which is necessary for formulating the prediction models of the eutrophication process development, being the basis of the elaboration of protecting strategies. The different combinations of input parameters were used to develop different models. The outcomes revealed from the model results that model-1 depends on the separate physical parameters, and showed the weak predictive power indicate that model 1, which relies on a limited set of physical variables (*T* and *WT*) in combination with the chemical parameter TN, demonstrates weak predictive power, while model-2 (including the nutrient and organic load parameters) demonstrated the improvement over model-1. The model-3, which is the integration of all parameters (TP, TN, PO_4^{3-}, NH_4^+, *COD* and season), showed the highest R^2 and correlation as compared to the other models in the initial train-test split (training R^2 = 0.197, testing R^2= 0.195, but still signifies a modest level of explanatory and does not clearly outperform model-2 when averaged across multiple folds. The permutation-based sensitivity analysis suggests that chemical oxygen demand (*COD*) and total phosphorus (TP) are the most influential predictors of the index of trophic state (*ITS*), which can be observed in model-2 and model-3, transparency (*T*), total nitrogen (TN), orthophosphate (PO_4^{3-}) and season on the other hand, show little contributions in the model-3, indicating that they provide additional but weaker information for the predicting eutrophication status.

However, the *k*-fold cross-validation outcomes confirm that all three models describe only a small proportion of variance in *ITS*, with a mean R^2 value around 0.06–0.11 and moderate correlation, whereas prediction errors (*RMSE* = 0.29–0.31, *MAE* = 0.22–0.23) remain relatively high. These outcomes revealed that under the current, small dataset, the ANNs obtain only limited structure in the *ITS* time series and should be interpreted as exploratory tools rather than robust forecasting models, signifying that the nutrient enrichment and seasonal dynamics of parameters are significant drivers of the eutrophication in Dal Lake (Sultan *et al.*, 2024). These outcomes harmonise with the recent study assessment of Dal Lake water chemistry, which revealed that growing concentrations of the nitrate-nitrogen and TP with time lead to a decline in dissolved oxygen in Dal Lake, indicating progressive eutrophication in the lake.

In the case of lake modelling, modellers need to put forward the problem of data insufficiency, which is a computational issue. The insufficient availability of water quality data is an issue discovered when applying machine learning techniques. To get good outcomes, the ANNs need to be trained with sufficient data (Hadjisolomou *et al.*, 2021). The ANN model reliability and performance were checked by using the *k*-fold cross-validation method, and the outcomes from the results showed that the performance of model-3 persisted reliably across different subsets of data, showing that its predictive ability is not simply an outcome of one specific data slice. The *k*-fold cross-validation has been suggested in ecological modelling to minimise the bias and to enhance the reliability of machine learning models (Yates, 2022). The sensitivity analysis based on the permutation importance was carried out. The outcomes revealed that among all input eutrophication factors *COD*, *WT*, and TN have the major impact on the trophic state expressed by the value of the *ITS*.

These outcomes concur with the study from Finland, which clearly demonstrates that the permutation importance is significantly effective in enumerating the parameters' impacts, that minimise the bias in mixed (numerical and categorical) eutrophication drivers being modelled (Heikonen, Yli-Heikkilä and Heino, 2023). This can be seen in Greece also, where in Lake Pamvotis, the water temperature and the soluble reactive phosphorus were considered as significant drivers of the chlorophyll a predictions by using an ANN model (Hadjisolomou *et al.*, 2016). Particularly in the Dal Lake, the trend of rising phosphorus and nitrogen loads together with degradation of water quality shows the importance of nutrient loading managing. The overall results of this study indicate that ANN models can help to recognise and classify the most influential drivers of the *ITS* in Dal Lake, but they do not provide reliable stand-alone predictions of eutrophication dynamics yet. Model-3 shows the relatively low power that signifies the complexity of the eutrophication dynamic processes. This recommends that the integration of additional ecological and biological parameters (e.g. chlorophyll a, algae, light penetration), probably also remote sensing data have ability to enhance the predictive ability of prior eutrophication factors. Comparable studies using ANN for lake eutrophication have often achieved higher R^2 once introducing the chlorophyll a and Secchi depth, as input or output parameters, together with the nutrients, organic matter and physical variables (Bhagowati *et al.*, 2022).

CONCLUSIONS

This study established three artificial neural network (ANN) models to evaluate the impact of selected eutrophication factors on the annual dynamics of the trophic status of the Dal Lake and to identify the most influential process drivers. Model-1, which is based on two physical parameters (*T* and *WT*) together with the chemical parameter TN, shows weak predictive power, while model-2 (nutrients and organic matter) showed only a slight improvement over model-1. Model-3, which combines (total phosphorus – TP, total nitrogen – TN, orthophosphate – PO_4, ammonium – NH_4, chemical oxygen demand – *COD* and season), explained the highest fit among all three models (R^2 = 0.197, R^2 = 0.195 in training and testing datasets, respectively) in the initial train-test split, but all the models show low explanatory power and *K*-fold cross-validation produced a mean R^2 value close to zero. These outcomes indicate that the present index of trophic state (*ITS*)-based ANN configurations capture only a small proportion of the trophic state variability and should be regarded as exploratory tools rather than operational forecasting models.

Despite this limited predictive capability, the sensitivity analysis consistently highlighted *COD* and TP, and to a lesser extent, TN, T, PO_4^{3-} and season, as the most influential inputs for the *ITS*. This suggests that organic matter, phosphorus, and nitrogen loads, together with the season, are key drivers of eutrophication development in the lake under current conditions. Together with the outcomes, these findings support the conclusion that the main factors controlling eutrophication in the Dal Lake are organic substances and nutrient inputs, particularly *COD*, TP and TN, and that improving the temporal and parameter coverage of water quality data will be essential for improving future ANN-based predictive models.

The low explanatory power of the models is due to the limited data availability and monitoring gaps in Dal Lake. The current long-term dataset does not have continuous, high-resolution data on several biological, chemical and hydrological parameters that are known to impact eutrophication, such as chlorophyll a, algal and macrophyte dynamics and detailed hydrodynamics. The uncertainties in measurements and irregular sampling further constrain the ability of empirical models to reproduce the observed *ITS* variability.

The development of robust eutrophication prediction tools for Dal Lake needs a more holistic monitoring strategy. The priority needs to be given to collecting high-resolution temporal data, expanding the set of ecological and physical parameters (including biological indicators), and integrating remote sensing and real-time monitoring techniques. The more advanced modelling approach, along with the use of spatial information from different lake basins, may substantially improve predictive accuracy and support management decisions.

CONFLICT OF INTERESTS

All authors declare that they have no conflict of interests.

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