Journal of
Water & Climate Change

© 2024 The Authors
Journal of Water and Climate Change Vol 15 No 8, 3724 doi: 10.2166/wcc.2024.032

Prediction of long-term changes of weak diurnal stratification in shallow lakes using artificial neural networks

Sebestyén Dániel Török [a] and Péter Torma [a,b,*]

[a] National Laboratory for Water Science and Water Security, Faculty of Civil Engineering, Department of Hydraulic and Water Resources Engineering, Budapest University of Technology and Economics, Budapest, Hungary
[b] HUN-REN–SZTE Research Group for Photoacoustic Monitoring of Environmental Processes, Szeged, Hungary
*Corresponding author. E-mail: torma.peter@emk.bme.hu

SDT, 0000-0003-1503-1021; PT, 0000-0001-9282-6931

ABSTRACT

Thermal stratification plays a key role in lakes' ecosystems. In contrast to deep lakes, the thermal structure of shallow polymictic lakes is characterized by a weak stratification with an apparent diurnal cycle. Long-term changes in stratification are governed by climate change and anthropogenic effects such as water level regulation. We developed a simple and robust model system consisting of an energy balance model to estimate depth-averaged water temperatures and an artificial neural network (ANN) model to predict stratification with high temporal resolution. One novelty of our approach is that instead of directly estimating water temperatures at different depths, we simulated the potential energy anomaly index, the indicator of stratification's strength. The ANN-based model's performance was assessed against a physical-based one-dimensional model (General Ocean Turbulence Model) by modeling a 40-year-long period from 1981 to 2020. The new model accurately predicts a shallow lake's weak stratification and its diurnal cycle. Besides, the model proved reliable on longer time scales, capturing the effect of climate change, anthropogenic water level regulation, and their synergistic interaction on the change of stratification's intensity and duration.

Key words: artificial neural network, climate change, diurnal stratification, potential energy anomaly, shallow lake, weak stratification

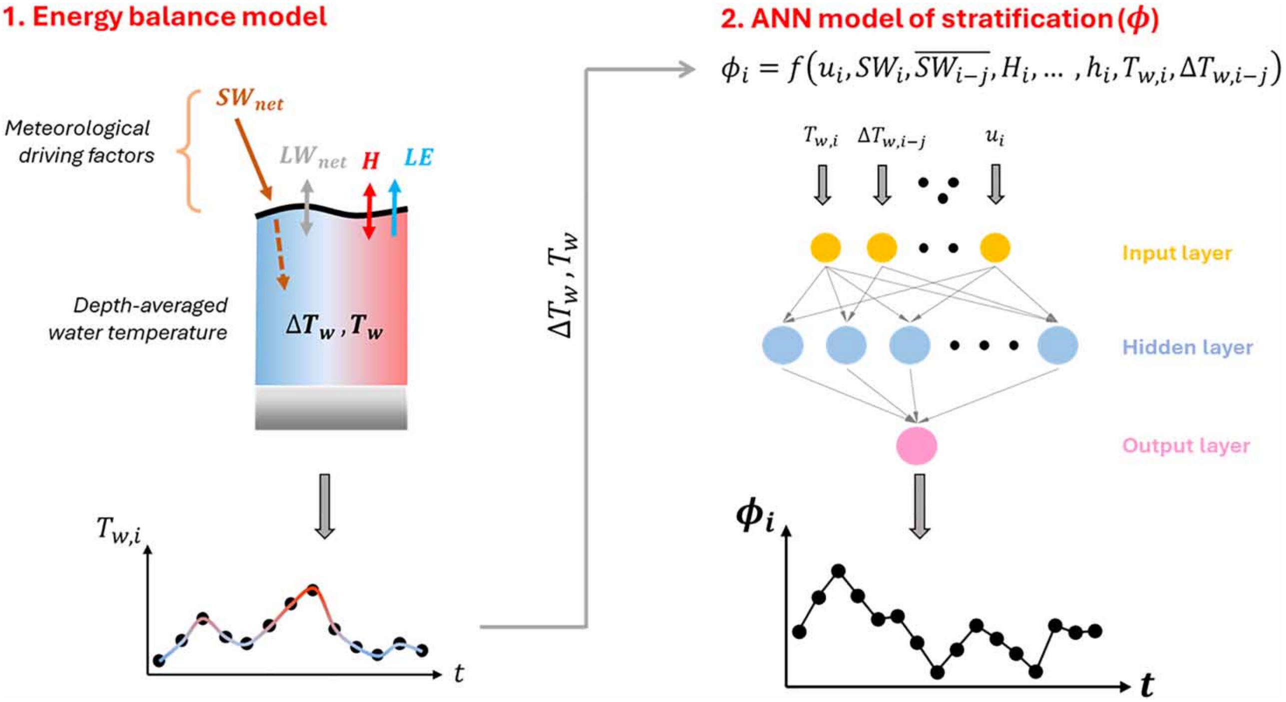
HIGHLIGHTS

- A simple energy balance and ANN model system is developed to simulate shallow lakes' stratification and evaluated using a physical-based model.
- Weak stratification is modeled with high temporal resolution to capture its diurnal lifecycle.
- The ANN-based model also reproduces the long-term synergistic impact of climate change and anthropogenic effects.

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

GRAPHICAL ABSTRACT



1. INTRODUCTION

Thermal stratification has a significant role in lakes' ecological status, potentially causing oxygen depletion at the lake's bottom. In deep lakes, when stratification occurs, the water column can be divided into three layers: epilimnion, hypolimnion, and thermocline. Out of these, the hypolimnion plays a crucial role in maintaining stratification, as in typical circumstances, low mixing characterizes this layer, allowing stratification to persist. As a result, oxygen depletion can develop over the bottom, leading to eutrophication through nutrient release (Pettersson *et al.* 2003; Salmaso 2005). In contrast, epilimnion and hypolimnion may not develop in shallow lakes because driving forces of mixing acting at the lake's surface can reach the bottom of the lake, resulting in more frequent mixing periods and shorter stratification durations (Wilhelm & Adrian 2008). The stratification usually lasts for months in deep lakes and ranges from hours to days in shallow lakes. Despite the frequent mixing, oxygen depletion can also develop in the latter case if meteorological conditions are met in such a way that an intermittent – a few days long – but continuous stratification develops, leading to severe ecological problems, such as the record-setting algae bloom in 2019 in Lake Balaton (Istvánovics *et al.* 2022). Thus, stratification can significantly influence the trophic state of shallow lakes (Shinohara *et al.* 2023).

In shallow lakes, meteorological effects can substantially affect stratification, so it is necessary to reveal their influence and their long-term changes (Zhou *et al.* 2023). The dominant driving forces of stratification are the solar radiation, the surface air temperature, and the wind speed. The former two are responsible for building up stratification by warming the water layers with different intensities, while the latter is mainly responsible for breaking it up by current- and wave-induced mixing processes (Torma & Krámer 2017). Just mentioning two examples, as a consequence of climate change, the number of lake heatwaves increases (Wang *et al.* 2023) as well as the intensity of evaporation (Tong *et al.* 2023). In mid-latitude climates, solar radiation, and surface air temperature tend to increase, warming lakes and prolonging stratification periods in the warm seasons (Woolway *et al.* 2020).

In addition to climate change, anthropogenic effects also have a significant impact on the stratification of lakes. Among the effects, those that result in a change in the water level should be highlighted, as the water depth plays a crucial role in the stability of stratification. The higher the depth, the more stable stratification can develop (Kraemer *et al.* 2015). Due to climate change, lake and reservoir water levels may decrease if precipitation and, as a result, runoff rates from the lake's watershed decrease. Consequently, stakeholders try to keep higher water levels to provide a puffer for drought periods. However, more

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

extended stratified periods can develop by a higher water level, increasing the possibility of oxygen depletion even in shallow, polymictic environments (Istvánovics *et al.* 2022).

In the case of shallow lakes, only weak stratification can develop with a typical diurnal cycle. This means that stratification develops over the day and breaks up due to surface cooling during the nighttime (Torma & Wu 2019). For example, in the very shallow Lake Balaton (Hungary), a stratification that forms over the day (with a maximum temperature difference of 5–6 °C between the surface and the bottom) mostly entirely disappears for the following day. Besides surface cooling, wind can also mix the water column through waves and currents, leading to even shorter stratified periods. Because of the diel cycle, at least hourly measurements are needed to capture the stratification in such environments. Nevertheless, in some cases, neither nighttime cooling nor the wind can mix the whole water column so that a stable stratification can continuously persist near the bottom for a few days. In such cases, anoxic conditions may occur with the consequences mentioned above. Overall, stratification and mixing processes in shallow lakes with a diurnal cycle must be modeled on short time scales of a few hours.

Physical-based models with different dimensions and empirical methods are also available to model stratification (Amorim *et al.* 2023; Naumenko & Guzivaty 2023). Due to the rapid growth of lake water temperature data, machine learning techniques, as powerful empirical tools, have gained immense potential and have been used more and more widely (Yousefi & Toffolon 2022). In contrast to physics-based models, machine learning techniques lack physical laws and theory; they make predictions based on data alone. One of their drawbacks arises from this, as their inaccuracy can increase if they are forced to make predictions for conditions outside the range used to train the model (Read *et al.* 2019). Nonetheless, various data-driven techniques, e.g., different artificial neural networks (ANNs), are successfully used to simulate the temperature conditions of lakes.

An ANN model can be a fast way to calculate water temperatures, and it is superior to regression models as they can accurately determine the nonlinear relationships between meteorological driving forces and water temperature changes. Nevertheless, they are usually used for deep lakes and reservoirs and mostly to predict lake water surface temperatures (Kimura *et al.* 2021; Wang *et al.* 2022). Regarding stratification, ANNs were only applied to simulate water temperatures at specific depths instead of directly determining stability conditions (Liu & Chen 2012; Saber *et al.* 2019; Saber *et al.* 2020). In short, based on a literature review, ANNs were not tested for polymictic lakes and for directly predicting stratification, even though they might be quick and reliable methods for these purposes.

The aim of this study is twofold. First, to prove that a simple artificial neural network model can simulate weak diurnal stratification for a shallow lake with high temporal resolution using routine meteorological data alone. Second, to show that an ANN model can quantify the long-term effects of climate change and anthropogenic impacts based on limited observational data.

2. MATERIALS AND METHODS

2.1. Study site and data acquisition

Lake Balaton is a shallow polymictic lake in Hungary, with a surface area of 596 km^2 and a mean depth of 3.2 m (Figure 1). Besides its ecological value, the lake is of great social and economic importance as it is highly populated along the whole shoreline and, after the capital, Hungary's second-most important tourist destination, providing many recreational activities like bathing, sailing, and fishing. It has an elongated shape, and in light of circulation and water quality patterns, it can be divided into four basins (Istvánovics & Honti 2018). The lake's main inflow is the Zala River, which accumulates the runoff from half of the total lake catchment (5.180 km^2) and flows into the westernmost basin. The lake has only one outflow in the eastern basin, which is regulated. The mean resident time is more than two years, and the role of throughflow is negligible for stratification, which is, therefore, almost uniquely shaped by meteorological forces.

Hydrometeorological measurements were carried out in the westernmost basin of the lake in the pelagic area in 2019, 2020, and 2022 in the warm season, from late spring to early autumn. The mean depth of this location was around 3.3 m for the three periods. During the measurement campaign, routine meteorological variables and water temperature profiles were recorded with high temporal resolution. The setup was very similar in each year. For 2019, detailed information about the lake, station location, and measurement setup can be found in Lükő *et al.* 2020 and 2022. The wind speed (U) was measured by CSAT3 and Windsonic2D anemometers (Campbell Sci.). The radiation components – incoming and outgoing shortwave (SW_{in}, SW_{out}) and longwave radiations (LW_{in}, LW_{out}) – were recorded by a CNR1 net radiometer (Kipp & Zonen). The air temperature (T_a) and relative humidity (RH) were measured by a HygroVue10 sensor (Campbell Sci.).

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

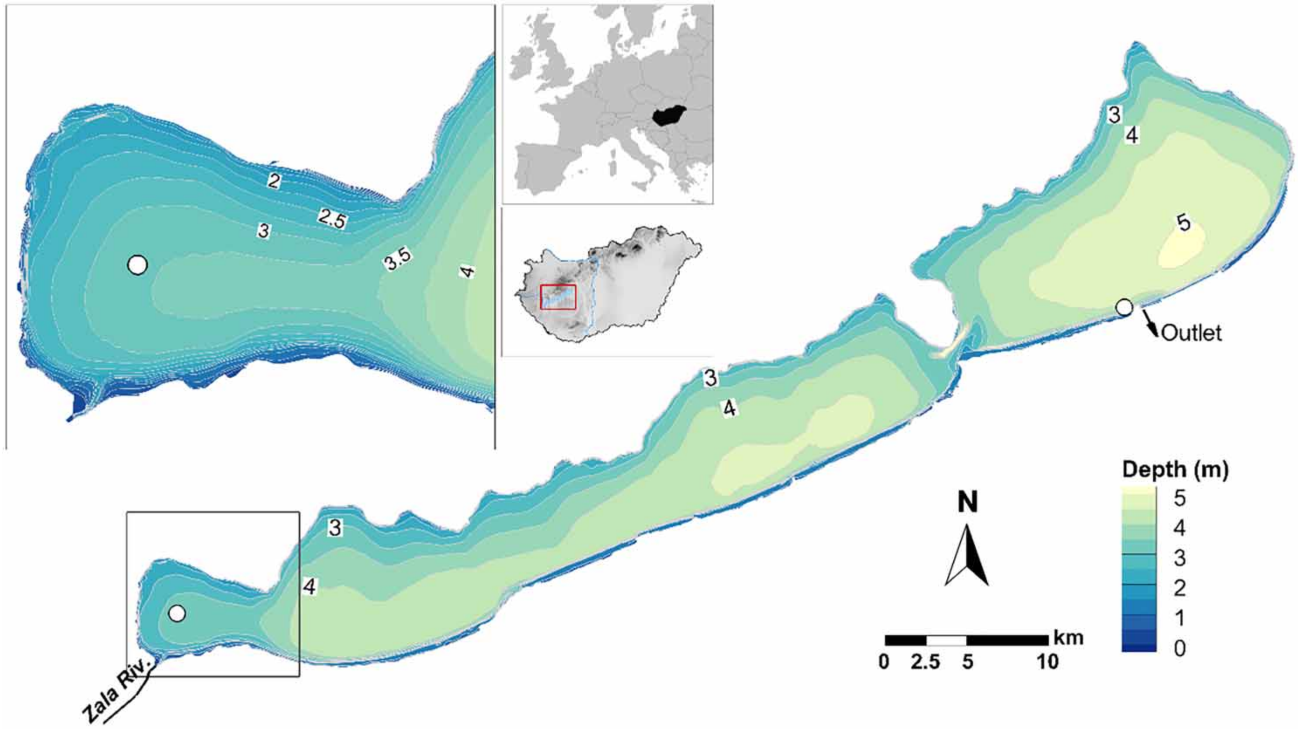


Figure 1 | Location and bathymetry map of Lake Balaton. Measurement sites are marked by white circles.

The water temperature profile was recorded by T107 sensors or a CS225-L thermistor string (both Campbell Sci.) at fixed depths with 0.5 m resolution. A floating sensor attached to a buoy 2 cm below the water surface measured the water surface temperature. During the campaign, both air and underwater instruments were regularly (2 weeks on average) checked, cleaned, and maintained.

In the easternmost basin of the lake, water temperature measurements were carried out by the Hungarian Meteorological Service between 1981 and 2020 near the south shoreline, where the average water depth is around 2.5 m. At this site, daily measurements were taken at a depth of 1 meter below the water surface. The stratification model was set up based on the measurements in the westernmost basin's open water area. In addition, the long-term daily data from the eastern basin was used to check the simulated daily average water temperatures (and thus the energy balance). It can be assumed that this eastern measurement is also representative due to the lake's relatively small thermal inertia and low spatial variability arising from the shallowness. Furthermore, the mean depth of the westernmost basin is around 2.5 m, which is equal to the depth at this eastern measurement location.

The long-term simulations covered a 40-year-long period from 1981 to 2020. For this period, the input meteorological data was gathered from the ECMWF ERA5 reanalysis database, including surface wind speed, wind direction, air temperature, RH, solar radiation, and downward longwave radiation with 1-h time resolution. Comparing the measured and ECMWF meteorological time series, bias correction was needed in the case of U, T_a, and SW_{in} variables. It has been performed by matching their cumulative distribution functions employing second-degree polynomials. Daily water level time series, from which monthly mean values were derived, was available from the Hungarian Water Directory.

2.2. ANN-based model system

For thermal stratification simulations, a simple model system was constructed with two submodules (Figure 2). The first submodule is a zero-dimensional (0D) energy balance model, which calculates the depth-averaged water temperatures (T_w) based on routine meteorological data following the energy balance equation:

$$R_n + H + LE = \rho_w \cdot c_{p,w} \cdot \frac{\partial T_w}{\partial t} \cdot h \tag{1}$$

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

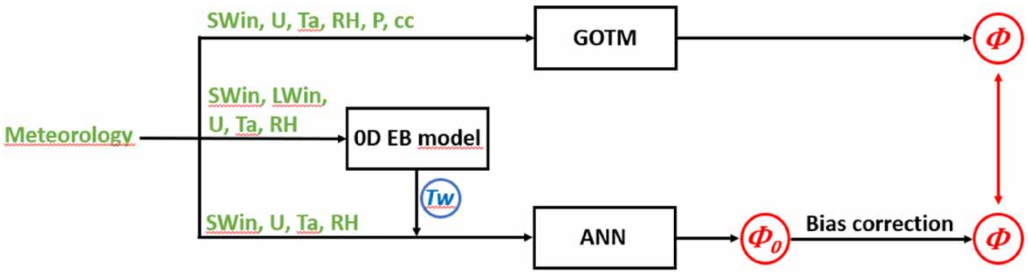


Figure 2 | Schematic drawing of the modeling process.

where R_n (W m^{-2}) is the net radiation, H and LE (W m^{-2}) are the turbulent sensible and latent heat fluxes, respectively, ρ_w (kg m^{-3}) is the density of water, $c_{p,w}$ (J kg^{-1} °C^{-1}) is the specific heat of water, t (h) is the time, and h (m) is the water depth. The turbulent heat fluxes were calculated by the following formulas (Lükő *et al.* 2022):

$$H = \rho_a \cdot c_p \cdot C_H \cdot U_z \cdot (T_a - T_w) \tag{2}$$

$$LE = \rho_a \cdot \lambda \cdot C_q \cdot U_z \cdot (q_z - q_0) \tag{3}$$

where ρ_a (kg m^{-3}) is the density of air, c_p (J kg^{-1} °C^{-1}) is the specific heat of air, λ is the heat of vaporization (J kg^{-1}), U_z (m s^{-1}) is the wind speed, T_a (°C) is the air temperature, q_z (kg kg^{-1}) is the specific humidity of the air, and q_0 (kg kg^{-1}) is the specific humidity at the surface. C_h and C_q are transfer coefficients, which were considered constants and calibrated. The 0D model works with hourly resolution.

The second module is an ANN model, which uses the water temperature and its temporal change obtained from the 0D model, routine meteorological data (U, T_a, RH, SW_{in}), and water depth (h) as inputs (Figure 2) and calculates the stratification index called the potential energy anomaly (ϕ) as output (see details in the following subchapter). It also uses the preceding 6-h average of U and SW_{in} to consider the dominant antecedent meteorological conditions for mixing and stratification, respectively. In the case of water depth, monthly averaged values were used. The model has one hidden layer and consists of six neurons. It is a nonlinear input-output network without using the estimated ϕ from the previous timestep.

The ANN model was trained for 3 years of data with a Bayesian regularization algorithm. The training and testing were done at 80–20%. Because of the Bayesian regularization, the validation process was unnecessary (Burden & Winkler 2009). The ANN model simulations were performed in the Matlab software environment. For stratification modeling, a 3-h time resolution was used as it was frequent enough to describe the daily cycle of stratification without considering the highly short-term fluctuations. After the training, historical simulations were carried out for four decades, from 1981 to 2020. Each year, the simulations were run from May to September to include the lake's warming up and cooling periods. In the results, only the summer months were examined. After the ANN simulations, a final bias correction was performed to improve the model's performance. A first-order polynomial was used for the correction, whose coefficients were calculated using the measured and trained data in 2019, 2020, and 2022.

2.3. Benchmark model

The calibrated 1D General Ocean Turbulence Model (GOTM, Burchard *et al.* 1999) was considered as a reference to assess the ANN m'del's reliability for long-term simulations. GOTM is a 1D model that uses a k-ε turbulence model for vertical mixing, providing stratification results on a physical basis. The model was driven by the same routine meteorological data as the 0D and the ANN model (Table 1). The sensible and latent heat fluxes were calculated by Equations (2) and (3) bulk formulas (Kondo 1975). The GOTM model has one further parameter to calibrate: the light extinction coefficient. In the absence of measurement data, we presumed it to be constant, and following a sensitivity analysis, it was set to 0.4 m^{-1}. For water depth, monthly averaged values were used. The water column was divided into 20 layers with an increasing resolution to the water surface and the bottom. The calibration and validation of the model were conducted for the years 2019 and 2022; after that, it was run for the 1981–2020 period with an hourly time resolution.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

Table 1 | Input and output variables and their avergaing time for the 0D energy balance, the ANN, and the reference GOTM models

			GOTM	EB	ANN
Input	SW_{in}	W m^{-2}	1 h_{avg}	1 h_{avg}	3 h_{avg}, 6 h_{avg}
	LW_{in}	W m^{-2}	-	1 h_{avg}	-
	U	m s^{-1}	1 h_{avg}	1 h_{avg}	3 h_{avg}, 6 h_{avg}
	T_a	°C	1 h_{avg}	1 h_{avg}	3 h_{avg}
	RH	%	1 h_{avg}	1 h_{avg}	3 h_{avg}
	P	hPa	1 h_{avg}	1 h_{avg}	-
	cc	-	1 h_{avg}	-	-
	T_w	°C	-	-	3 h_{avg}
Output	T_w	°C	3 h_{avg} (in 20 depths)	3 h_{avg}	-
	ϕ	J m^{-3}	3 h_{avg}	-	3 h_{avg}

1 h_{avg} stands for hourly, 3 h_{avg} for three-hourly, and 6 h_{avg} for six-hourly averages.

2.4. Evaluation of model performance

The intensity and duration of stratification are assessed through the potential energy anomaly index (ϕ, J m^{-3}), which gives the energy needed to fully mix the stratified water column (Wiles *et al.* 2006; Istvánovics *et al.* 2022). The potential energy anomaly can be calculated as follows:

$$\phi = \frac{g}{h}\int_0^h [\bar{\rho} - \rho(z)]z dz \tag{4}$$

where g (m s^{-2}) is the gravitational acceleration, h (m) is the water depth, ρ (kg m^{-3}) is the density of the water, $\bar{\rho}$ (kg m^{-3}) is the mean water density, and z (m) is the vertical coordinate. Figure 3 shows an example of ϕ together with the measured water temperatures at different depths.

The models' performance was evaluated through three statistical indicators: the root mean square error (RMSE), the Nash–Sutcliffe Efficiency (NS), and the relative deviation (Δ_{rel}). They were calculated as follows:

$$\text{RMSE} = \sqrt{\sum \frac{(\hat{y}_i - y_i)^2}{n}} \tag{5}$$

$$NS = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \overline{y}_i)^2} \tag{6}$$

$$\Delta_{rel} = \frac{\sum (\hat{y}_i - y_i)}{\sum y_i} \cdot 100 \tag{7}$$

where y and $\hat{y}$ are the observed and simulated data, while n is the number of observations.

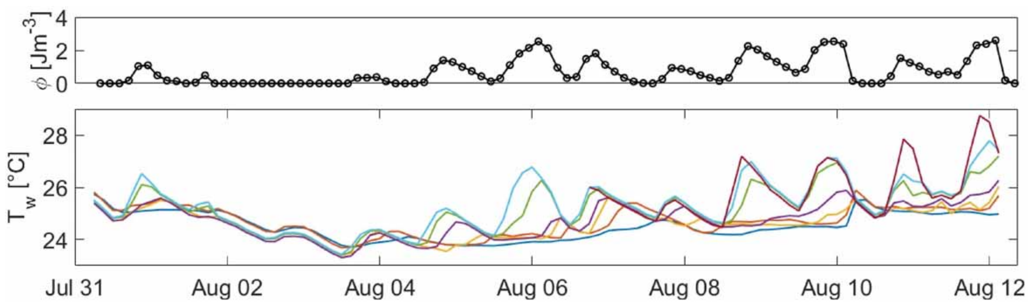


Figure 3 | Daily cycle of measured water temperatures at different depths and the corresponding potential energy anomaly (ϕ) time series.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

3. RESULTS

3.1. Meteorological and hydrological conditions

In the last 40 years, increasing trends have been experienced in the case of wind speed (0.006 m s^{-1}/10 year), incoming short-wave radiation (4.44 W m^{-2}/10 year), and air temperature (0.50 °C/10 year) during the summer months (June-August), which are the main factors of stratification formation and break-up. Along with these, water temperature shows a slightly weaker increasing trend than air temperature, having a warming rate of 0.44 °C/10 year (Figure 4).

The mean water depth of Lake Balaton for the summer months in the 1980s was 3.21 m, but after some drought periods in the early 2000s – between 2000 and 2003 – it dropped to 2.93 m (Figure 4). The lowest summer water depth was recorded in August 2003, at 2.63 m. After that, water level regulation was made for the lake, and the maximum control water level was increased by 10 cm. It took three years for the lake to reach the new regulation level, so its effect can only be seen starting in 2006. In 2016, due to a new regulation, it has been increased by 10 cm again. Accordingly, the mean water depth for the summer months between 2006 and 2015 was 3.31 m, while from 2016 to 2020, 3.43 m.

3.2. Calibration and validation

The reference GOTM model was calibrated and validated for two parameters – T_w and ϕ – for 2019 and 2022. For depth-averaged water temperature, the model provides good results, with a slight overestimation in the case of sudden cooling periods. In the case of an unstable stratification (resulting in negative ϕ values), the model immediately mixes the water column and couldn't reproduce unstable situations. However, these events are negligible in the summer because they cannot last long and are very weak. Therefore, the rarely occurring negative ϕ values produced by the ANN were also neglected. Overall, the model provided satisfactory results for T_w and ϕ, which made it suitable for further investigations. Table 2 shows the statistical indicators for the calibration and validation periods regarding the two parameters.

The 0D energy balance model was calibrated for 2019, validated for 2020, and then run for the 1981–2020 period. The modeled hourly temperatures were averaged to daily means and compared with the measured ones in the eastern basin. Figure 5 shows the NS and RMSE values for the modeled water temperatures for each year. On average, the NS is above 0.75, and the RMSE is between 1 and 2 °C. There are 4 years of exception (1984, 1985, 1993, and 2001). In these years, the NS and RMSE values are significantly worse. According to the notice obtained from the authority, measurement inaccuracies might have occurred in these years as the temperature sensor likely sank into the sediment.

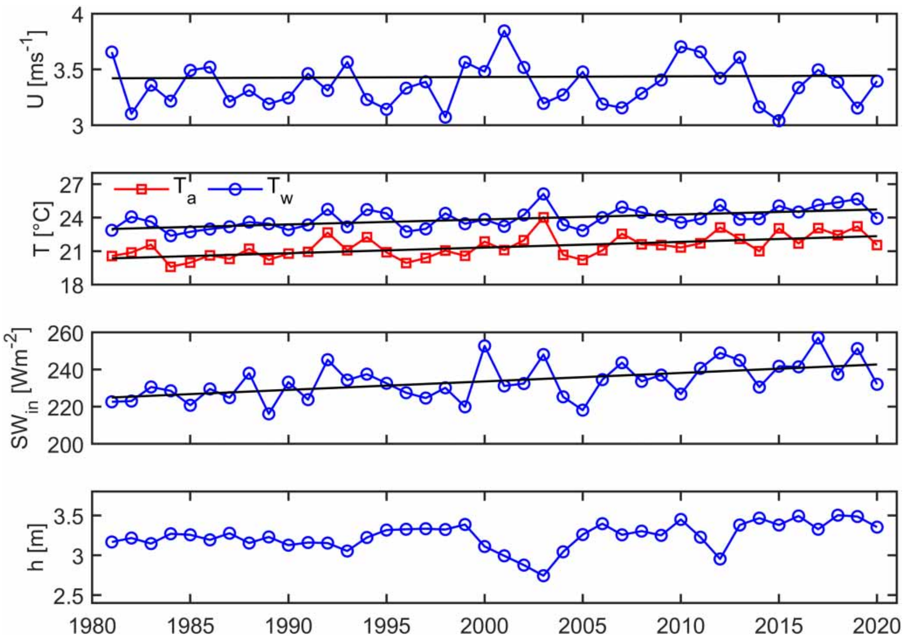


Figure 4 | Yearly summer averaged values of U, T_a, T_w, SW_{in}, and h between 1981 and 2020 in Hungary.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

Table 2 | Statistical indicators of the calibration and validation periods for the 0D energy balance, the ANN, and the reference GOTM models

		Calibration/Training			Validation		
		NS	RMSE	Δ_{rel}	NS	RMSE	Δ_{rel}
0D EB	T_w	0.85	1.07	0.15	0.78	1.51	3.3
ANN	ϕ	0.65	0.54	3.99	-	-	-
GOTM	T_w	0.81	1.37	0.98	0.91	0.96	0.98
	ϕ	0.63	0.72	0.76	0.45	0.57	0.81

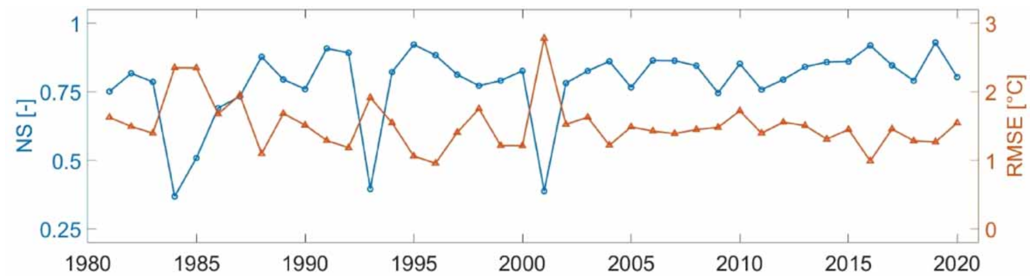


Figure 5 | NS and RMSE values for the 0D m'del's water temperature simulation from 1981 to 2020.

The ANN model was trained and tested for the potential energy anomaly index for 2019, 2020, and 2022. The results were compared with the ϕ values calculated from the field measurements at the western basin and by the GOTM model (Figure 6). It can be seen that the ANN reproduces the measurement well, providing very similar results as the GOTM model and resulting in appropriate goodness-of-fit indices (Table 2). It must be noted that the training/testing period covered a limited range of water depths (60 cm), from 2.98 m to 3.58 m, while monthly mean water depths varied between 2.6 m–3.55 m (92 cm) during the 40-year-long period.

Comparing the measured and simulated potential energy anomaly time series, it was found that both GOTM and ANN can qualitatively follow the course of the diurnal cycle of weak stratification. A representative period is shown in Figure 7. In the case of higher ϕ values, the ANN underestimated the measured ones several times. This was resolved by the bias correction as a final step (Figure 2). Comparing the two models, the ANN model proved to be slightly worse overall, but there have been many periods when ANN's estimations were closer to observations, e.g., on the 5th and 7th of August (Figure 7).

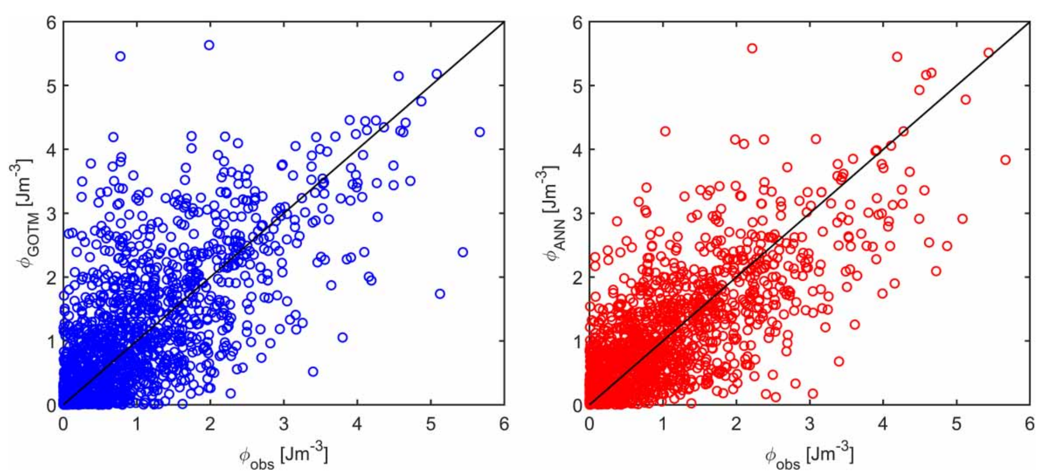


Figure 6 | Comparison of the measured and simulated ϕ values. Right: comparing with the GOTM. Left: comparing with the ANN.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

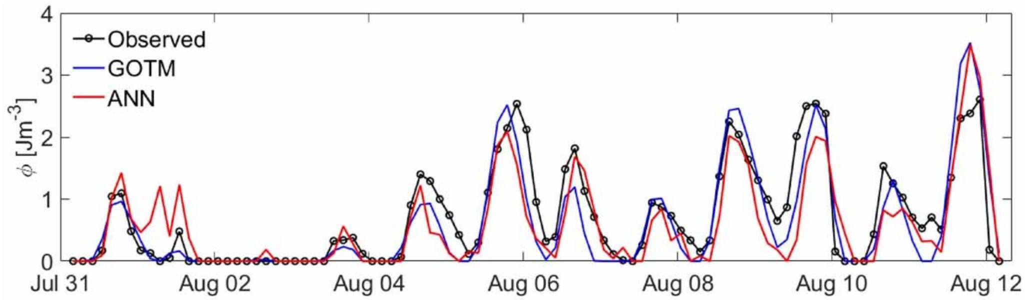


Figure 7 | Measured and simulated ϕ time series between 08.01.2019 and 08.13.2019.

3.3. Long-term simulations

Along with the meteorological conditions, an increasing trend can also be seen in the strength of the lake's thermal stratification during the summer months over the last 40 years. This was somewhat expected since those meteorological forces (T_a, SW_{in}), which are responsible for stratification formation, possess more significant growth rates than wind speed, the main driver of mixing. However, the intensity and duration of stability changes were unknown in the absence of long-term observed water temperature profiles. Figure 8 shows the median potential energy anomaly values for the summer periods for each year. IThe whole period was divided into two to separate the effects of climate change and water level regulation. Accordingly, the first period was from 1981 to 2006 – before the water level control could have its effect – while the second one was from 2007 to 2020. In both cases, increasing trends can be observed; however, after the regulation, the steepness of growth increases, meaning that the water depth significantly affects stratification even by a few 10 cm changes. When assessing the long-term impact of climate change and water depth variations, the ANN model demonstrated the same trends as the physics-based one. Regarding the water level periods (1981–2006 and 2007–2020), the trends given by the GOTM are 0.03 and 0.14 J m^{-3}/10 years, while the ANN model resulted in 0.04 and 0.17 J m^{-3}/10 years trends, respectively, which are nearly identical. Looking at the cumulative distribution functions of ϕ for each summer (Figure 9), it could also be concluded that the ANN model tended to overestimate the GOTM-based values at weak stratifications ($\phi < 0.6$). Finally, the early 2000s should also be noted, when a three-year-long drought period resulted in extremely low water depths, which were out of the depth range used in the training/testing. However, the ANN model could predict stratification similarly to the GOTM model.

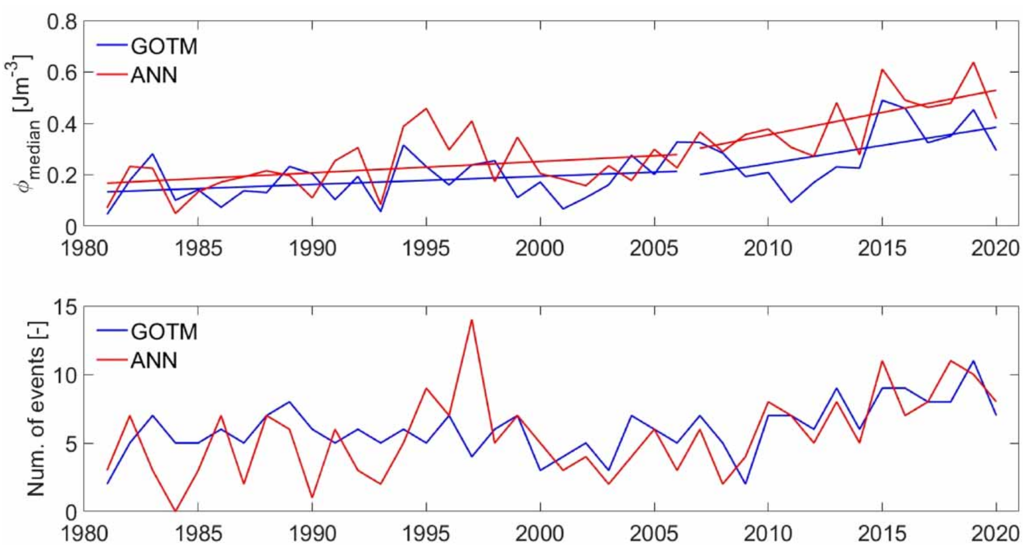


Figure 8 | Upper: yearly median of summer ϕ values between 1981 and 2020. Lower: number of stratification periods between 1981 and 2020, when the stratification lasted at least 24 h, with a threshold of 0.5 J m^{-3}.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

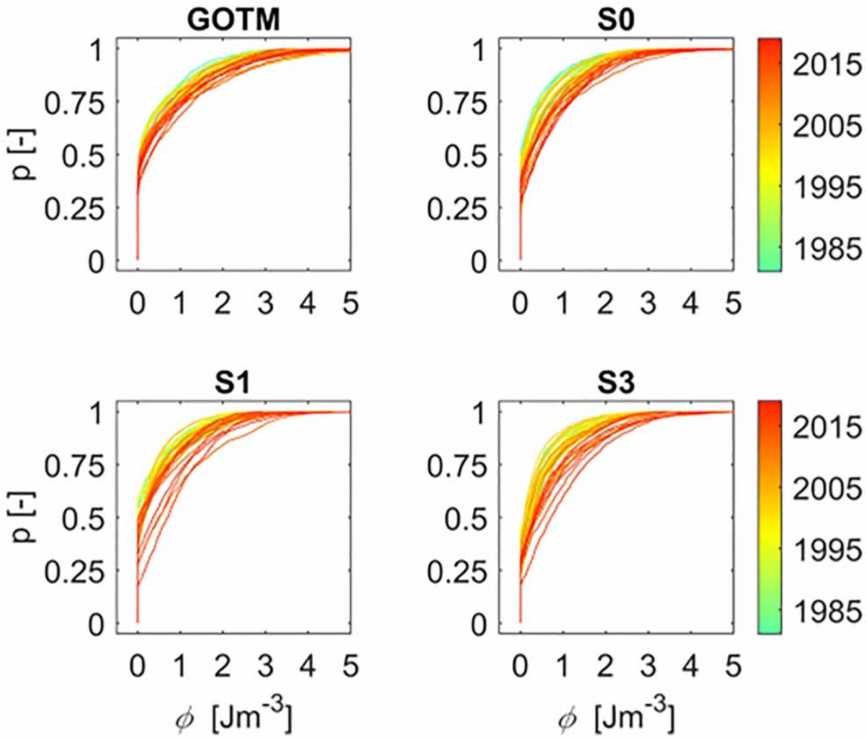


Figure 9 | Empirical cumulative distribution functions for the GOTM and the ANN training cases between 1981 and 2020.

As mentioned in the Introduction, periods when stratification does not entirely vanish by the next day may be crucial in the lake's ecology. Thus, the number of stratification periods that lasted at least 24 h were looked at using two different thresholds, 0.5 and 1.0 J m^{-3}. In both cases, similar increasing trends experienced. The thresholds were selected to ensure that the stratification would exhibit sufficient strength to be classified as stable. Figure 8 shows how the number of stratified periods evolved in the last 40 years for the 0.5 J/m^3 limit.

Both models showed the same tendencies. The GOTM resulted in 5.4 and 7.2 events per year for the two water depth periods, while the ANN gave 4.8 and 7.1 events, respectively. In contrast to the summer median ϕ values, the number of events didn't possess an increasing trend before 2006, meaning that climate change-related intensification of stratification was not strong enough to maintain a stable thermal structure that could survive by the next day. It also has to be mentioned that till 1997, the ANN model suggested a higher variability, having also years without 1-day-long stratification periods. This can be partly explained by the relationship between water depth and light extinction (see Discussion). Overall, the ANN model can assess the same trends for more extended stratification periods as the physics-based GOTM and adequately captures the interactive effect of water depth increase and climate change from 2006.

4. DISCUSSION

4.1. The effects of natural and anthropogenic driving forces

Lake Balaton's thermal stratification is primarily driven by wind speed, incoming shortwave radiation, and air temperature, which all show an increasing trend (Figure 4). SW_{in} and T_a are working in favor of the stratification by increasing vertical water temperature and density differences. In contrast, the U works against it by inducing waves and currents, which make the water column mix and the stratification dissipate. Considering their integrated effect, an increasing trend can be seen in the strength of the lake's thermal stratification (Figure 8), which was captured by the ANN model with a suitable accuracy (Figure 7). Water depth also has a crucial effect on the stratification, as it not only increases its strength but amplifies the impact of climate change. As a result, the observed increasing trend after 2006 is a combined, synergistic effect of the varying climate and the heightened water levels. This interaction increases not just the average stability but also results in longer-lasting stratification, and with this, the 24-h-long events occur more and more often.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

Turbidity also greatly affects the lake's stratification. In the case of turbid water, incoming shortwave radiation can penetrate only to a limited depth, warming up only the layers it manages to traverse. This creates a temperature difference between the layers, contributing to the development of stratification. In the other case, when the water is more transparent, solar radiation can penetrate deep and warm up the whole water column, so the temperature difference between the layers will be slighter, resulting in a very weak stratification. Light extinction (or attenuation coefficient), which quantifies the efficiency of water absorbing the incoming light, depends linearly on turbidity (Brown 1984). Turbidity, and thus water transparency, is determined by the concentration of organic and inorganic substances, like phytoplankton and suspended sediments, respectively. As a result, light extinction is a highly variable parameter both on small and large time scales. However, external factors such as meteorology also directly and strongly determine it.

In the case of smaller water depths, sediment resuspension can occur more often as the wind-induced mixing can reach the lake's bottom more quickly and with higher intensity, resulting in more variable water transparency conditions. In the ANN model, this might be indirectly incorporated through nonlinear relationships with wind forcing. Regarding the 1-day-long stratification events, the ANN model showed higher variability for the first period (1981–2006) with lower water levels. In contrast, light attenuation was fixed to a constant in the GOTM model. For example, on the 4th and 5th of August, GOTM underestimated ϕ, and the ANN model provided better results (Figure 7). These two days were preceded by a wind event, likely with sediment resuspension. The suspended fine sediments require quite a long time to settle, and until that, they result in higher turbidity, light attenuation, and stratification, as explained above. This means that in some cases, the ANN may provide better results than the GOTM, even though the latter operates on a physical basis.

4.2. Sensitivity of training parameters

Sensitivity analysis was carried out on three main elements of the ANN model setup: (i) the role of the water depth range in the training, (ii) the quantity of the training data, and (iii) the role of antecedent wind and solar radiation conditions. The model was trained using 3 years of data: 2019, 2020 and 2022. This version is referred to as S0. For (i) and (ii), the model was trained with only 2 years of data and then ran it for all the 3 years. The S1 model version was trained for 2019 and 2022, with a wide range of water depths, while the S2 model version was trained for 2019 and 2020 when water levels were significantly higher than in 2022. To assess the differences between the training cases the NS efficiency was used (Table 3).

In 2019 and 2020, the water level was high; the depth varied between 3.55 and 3.30 m at the measurement station, while in 2022, it was between 3.32 and 2.98 m. Due to this difference in water depths, the S2 model had to perform extrapolation for almost the whole of 2022. As a result, the S2 model mostly underestimated ϕ and provided unreliably strong, unstably stratified periods. In the S1 case, the water depth in the training period covered the whole range of the 3-years, so the model did not have to extrapolate. Compared to the accepted S0 version, the NS worsened by less than 5% due to the reduced training data providing fewer possible meteorological states (Table 3). Since the difference between S0 and S1 was not convincing for the three years, both models were run for the 1981–2020 period and compared based on the cumulative distribution functions. The distribution of the S1 case shows a more considerable variability than the one obtained using GOTM or the S0 version (Figure 9). In our case, this means that the S1 version is unreliable and usually overestimates the strength of stratification. However, the three-year dataset proved sufficient to establish reliable connections between meteorological driving factors and thermal structure.

Lastly, a simple sensitivity analysis was made for SW_{in} and U as the most dominant driving forces of stratification formation and break-up, respectively. In the S0 model, the input data included the mean U and SW_{in} from the preceding 6 h besides their instantaneous values. Since the NS index declined by only 8% for three years of training, the model was run without

Table 3 | NS values of the different training cases

Version	Training years	NS [–]	preceding SW_{in}, U conditions
S0	2019, 2020, and 2022	0.65	yes
S1	2019 and 2022	0.62	yes
S2	2019 and 2020	0.59	yes
S3	2019, 2020, and 2022	0.60	no

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

the averaged values for the 1981–2020 period. As a result, the cumulative distribution functions again possess a more significant variability than the physics-based GOTM model. This means that even though the statistical indicators do not clearly support the usage of the 6-h averaged values, they are not negligible because their impacts become pronounced when we consider the long-term changes.

5. CONCLUSIONS

Machine learning recently became a common and efficient tool for simulating, hindcasting, and predicting lakes' water temperature. A very simple and, thus, robust model has been developed that can simulate shallow lakes' weak stratification and its diurnal cycle with similar accuracy to a complex physics-based 1D model. The presented model system possesses two submodules, both forced by the same routine meteorological variables. The first submodule is a 0D energy balance model, which estimates the depth-averaged water temperature and its temporal change as further inputs for the ANN submodule. As its output, the ANN model calculates the potential energy anomaly index, which characterizes the strength of thermal stratification. The model proved to be reliable both on short and long time scales. Besides capturing the diurnal variation and the intensity of stratification, it was able to explore the effect of climate change, anthropogenic water level regulation, and the synergistic interaction of these two.

Our study provides at least two main novelties. First, it proves that a simple ANN model can simulate a delicate environment with rapidly changing and weak stratification conditions. Of course, to train the model, it is required to have a suitably long and high-frequency time series, including both temperature profiles and meteorological variables. In our case, the time series from three summer seasons proved sufficient. Second, instead of directly estimating water temperature in different depths, the potential energy anomaly index was simulated that adequately describes a shallow lake's stratification. Water temperatures are estimated based on the energy balance equation, which requires only routine meteorological data, and its calibration is also straightforward. This method also has the advantage that water temperature estimates satisfy the energy conservation in contrast to temperatures estimated by machine learning techniques.

The ANN model's predictivity can be improved in the future. Firstly, the hydrometeorological measurements have continued in Lake Balaton, so the training dataset can be extended with further seasons. Secondly, the most simple ANN structure was used for the modeling. It is conjectured that the ANN model's accuracy will increase by including estimated ϕ values from previous time steps in the inputs. Similarly, real-time in-situ measurements can be easily introduced to such a system, making it suitable for nowcasting purposes. Finally, if turbidity or light extinction data are also available, a more complex system would be worth establishing that estimates turbidity conditions first and stratification in a second step. The simultaneous availability of these two parameters would also be fruitful for simulating habitat conditions.

The proposed model system offers an efficient tool for examining several changes in shallow lake environments in the long term. The ANN model can capture intra-daily stratification and its alteration by slowly varying climate change-driven meteorological forces and by much faster human interventions like water level regulation, incorporating their synergistic effect, too. Since the system includes an energy balance submodule, evaporation changes can also be tracked. Evaporation plays a crucial role in the lake's water resource as it is the main loss component of the water balance. For water resources management, accounting for the changes in stratification and evaporation is inevitable, and this model system offers a simple and fast method for their joint calculation. In light of these changes, stakeholders can make informed decisions to ensure sustainable management of the lake's environment.

ACKNOWLEDGEMENTS

The research presented in the article was carried out within the framework of the Szechenyi Plan Plus program with the support of the RRF 2.3.1 21 2022 00008 project. This research was also funded by the Ministry of Culture and Innovation and the National Research, Development and Innovation Office (Grant Nr: TKP2021-NVA-02 and K134559). In the case of the first author, the project was supported by the Doctoral Excellence Fellowship Programme (DCEP) is funded by the National Research Development and Innovation Fund of the Ministry of Culture and Innovation and the Budapest University of Technology and Economics, under a grant agreement with the National Research, Development and Innovation Office. Finally, for the second author, funding was also provided by the Hungarian Academy of Sciences (Award: Janos Bolyai fellowship 00906/23).

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Amorim, L., Duarte, B. & Martins, J. 2023 Comparison between methods to predict climate change impacts on tropical shallow lakes. *Journal of Water and Climate Change* **14** (2), 4299–4313. 10.2166/wcc.2023.100.

Brown, R. 1984 Relationships between suspended solids, turbidity, light attenuation, and algal productivity. *Lake and Reservoir Management* **1** (1), 198–205. https://doi.org/10.1080/07438148409354510.

Burchard, H., Bolding, K. & Ruiz-Villarreal, M. 1999 *GOTM, A General Ocean Turbulence Model. Theory, Implementation and Test Cases*, Report EUR 18745, European Commission, Brussels, Belgium.

Burden, F. & Winkler, D., 2009 Bayesian Regularization of Neural Networks. In: *Artificial Neural N–Tworks – Methods and Applications* (Livingstone, D. J., ed.). Humana Press, Totowa, New Jersey, pp. 23–42. https://doi.org/10.1007/978-1-60327-101-1.

Istvánovics, V. & Honti, M. 2018 Coupled simulation of high-frequency dynamics of dissolved oxygen and chlorophyll widens the scope of lake metabolism studies. *Limnology and Oceanography* **63** (1), 72–90. https://doi.org/10.1002/lno.10615.

Istvánovics, V., Honti, M., Torma, P. & Kousal, J. 2022 Record-setting algal bloom in polymictic Lake Balaton (Hungary): A synergistic impact of climate change and (mis)management. *Freshwater Biology* **67** (6), 1091–1106. https://doi.org/10.1111/fwb.13903.

Kimura, N., Ishida, K. & Baba, D. 2021 Surface water temperature predictions at a Mid-Latitude reservoir under long-Term climate change impacts using a deep neural network coupled with a transfer learning approach. *Water* **13** (8), 1109. https://doi.org/10.3390/w13081109.

Kondo, J. 1975 Air-sea bulk transfer coefficients in diabatic conditions. *Boundary-Layer Meteorology* **9**, 91–112. https://doi.org/10.1007/BF00232256.

Kraemer, B. M., Anneville, O., Chandra, S., Dix, M., Kuusisto, E., Livingstone, D. M., Rimmer, A., Schladow, S. G., Silow, E., Sitoki, L. M., Tamatamah, R., Vadeboncoeur, Y. & McIntyre, P. B. 2015 Morphometry and average temperature affect lake stratification responses to climate change. *Geophysical Research Letters* **42** (12), 4981–4988. https://doi.org/10.1002/2015GL064097.

Liu, W.-C. & Chen, W.-B. 2012 Prediction of water temperature in a subtropical subalpine lake using an artificial neural network and three-dimensional circulation models. *Computers & Geosciences* **45**, 13–25. https://doi.org/10.1016/j.cageo.2012.03.010.

Lükő, G., Torma, P., Krámer, T., Weidinger, T., Vecenaj, Z. & Grisogono, B. 2020 Observation of wave-driven air–water turbulent momentum exchange in a large but fetch-limited shallow lake. *Advances in Science and Research* **17**, 175–182. https://doi.org/10.5194/asr-17-175-2020.

Lükő, G., Torma, P., Weidinger, T. & Krámer, T. 2022 Air-lake momentum and heat exchange in very young waves using energy and water budget closure. *Journal of Geophysical Research Atmospheres* **127** (12), e2021JD036099. https://doi.org/10.1029/2021JD036099.

Naumenko, M. & Guzivaty, V. 2023 Seasonal evolution of stable thermal stratification in central area of Lake Ladoga. *Limnological Review.* **23** (3), 177–189. https://doi.org/10.3390/limnolrev23030011.

Pettersson, K., Grust, K., Weyhenmeyer, G. & Blenckner, T. 2003 Seasonality of chlorophyll and nutrients in Lake Erken –effects of weather conditions. *Hydrobiologia* **506**, 75–81. https://doi.org/10.1023/B:HYDR.0000008582.61851.76.

Read, J. S., Jia, X., Willard, J., Appling, A. P., Zwart, J. A., Oliver, S. K., Karpatne, A., Hansen, G. J. A., Hanson, P. C., Watkins, W., Steinbach, M. & Kumar, V. 2019 Process-Guided deep learning predictions of lake water temperature. *Water Resources Research* **55** (11), 9173–9190. https://doi.org/10.1029/2019WR024922.

Saber, A., James, D. E. & Hayes, D. F. 2019 Estimation of water quality profiles in deep lakes based on easily measurable constituents at the water surface using artificial neural networks coupled with stationary wavelet transform. *Science of The Total Environment* **694**, 133690. https://doi.org/10.1016/j.scitotenv.2019.133690.

Saber, A., James, D. E. & Hayes, D. F. 2020 Long-term forecast of water temperature and dissolved oxygen profiles in deep lakes using artificial neural networks conjugated with wavelet transform. *Limnology and Oceanography* **65** (6), 1297–1317. https://doi.org/10.1002/lno.11390.

Salmaso, N. 2005 Effects of climatic fluctuations and vertical mixing on the interannual trophic variability of Lake Garda, Italy. *Limnology and Oceanography* **50** (2), 553–565. https://doi.org/10.4319/lo.2005.50.2.0553.

Shinohara, R., Matsuzaki, S.-I. S., Watanabe, M., Nakagawa, M., Yoshida, H. & Kohzu, A. 2023 Heat waves can cause hypoxia in shallow lakes. *Geophysical Research Letters* **50**, e2023GL102967. https://doi.org/10.1029/2023GL102967.

Tong, Y., Feng, L., Wang, X., Pi, X., Xu, W. & Woolway, R. I. 2023 Global lakes are warming slower than surface air temperature due to accelerated evaporation. *Nature Water* **1**, 929–940. https://doi.org/10.1038/s44221-023-00148-8.

Torma, P. & Krámer, T. 2017 Modeling the effect of waves on the diurnal temperature stratification of a Shallow Lake. *Periodica Polytechnica Civil Engineering* **61** (2), 165–175. https://doi.org/10.3311/PPci.8883.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest

Torma, P. & Wu, C. 2019 Temperature and circulation dynamics in a small and shallow lake: Effects of weak stratification and littoral submerged macrophytes. *Water* **11** (1), 128. https://doi.org/10.3390/w11010128.

Wang, L., Xu, B., Zhang, C., Fu, G., Chen, X., Zheng, Y. & Zhang, J. 2022 Surface water temperature prediction in large-deep reservoirs using a long short-term memory model. *Ecological Indicators* **134**, 108491. https://doi.org/10.1016/j.ecolind.2021.108491.

Wang, X., Shi, K., Zhang, Y., Qin, B., Zhang, Y., Wang, W., Woolway, R. I., Piao, S. & Jeppesen, E. 2023 Climate change drives rapid warming and increasing heatwaves of lakes. *Science Bulletin* **60** (14), 1574–1584. https://doi.org/10.1016/j.scib.2023.06.028.

Wiles, P. J., van Duren, L. A., Häse, C., Larsen, J. & Simpson, J. H. 2006 Stratification and mixing in the Limfjorden in relation to mussel culture. *Journal of Marine Systems* **60** (1–2), 129–143. https://doi.org/10.1016/j.jmarsys.2005.09.009.

Wilhelm, S. & Adrian, R. 2008 Impact of summer warming on the thermal characteristics of a polymictic lake and consequences for oxygen, nutrients and phytoplankton. *Freshwater Biology* **53** (2), 226–237. https://doi.org/10.1111/j.1365-2427.2007.01887.x.

Woolway, R. I., Kraemer, B. M., Lenters, J. D., Merchant, C. J., O'reilly, C. M. & Sharma, S. 2020 Global lake responses to climate change. *Nature Reviews Earth & Environment* **1**, 388–403. https://doi.org/10.1038/s43017-020-0067-5.

Yousefi, A. & Toffolon, M. 2022 Critical factors for the use of machine learning to predict lake surface water temperature. *Journal of Hydrology* **606**, 127418. https://doi.org/10.1016/j.jhydrol.2021.127418.

Zhou, J., Leavitt, P. R., Rose, K. C., Wang, X., Zhang, Y., Shi, K. & Qin, B. 2023 Controls of thermal response of temperate lakes to atmospheric warming. *Nature Communications* **14**, 6503. https://doi.org/10.1038/s41467-023-42262-x.

First received 3 January 2024; accepted in revised form 13 June 2024. Available online 5 July 2024

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/8/3724/1473980/jwc2024032.pdf
by guest