

A lightweight deepwater oxygen model for investigating lake responses to future climate

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ARTICLE INFO

Keywords:

Deepwater oxygen
Future projections
Climate change
Management framework
Oxygen stability
Lake Erken

ABSTRACT

Climate-driven deepwater deoxygenation is a growing global concern for lake ecosystems. We developed a simple 1-D deepwater oxygen profile model to understand the underlying physical mechanisms and to quantify the required climate-adaptive interventions. It was applied to Lake Erken, Sweden, using hydrodynamic forcing under three Representative Concentration Pathway (RCP) scenarios. From 2020 to 2099, the annual anoxic factor (the number of days when the anoxic sediment area equals the lake surface area) projections show non-significant trends under RCP2.6, while increasing by 0.4 and 0.6 days year⁻¹ decade⁻¹ under RCP6.0 and RCP8.5, respectively. This climate-driven future deoxygenation, consistent across multiple oxygen metrics, mainly stems from prolonged stratification. To mitigate climate impacts by 2100, oxygen depletion rates, as a proxy for eutrophication, would need to be reduced by approximately 9–13%, 20–24% and 26–35% under RCP2.6, RCP6.0 and RCP8.5, respectively. This data-efficient framework can be applied to physically-dominated, seasonally stratified lakes.

1. Introduction

Dissolved oxygen (DO) is a fundamental indicator of water quality and a key regulator of lake ecosystem functions, such as drinking water supply, recreational activities and biodiversity (Carey, 2023; Gee et al., 1997; Hutchinson, 1957; Marcé et al., 2023). Despite its importance for maintaining lake health (Hutchinson, 1957; Marcé et al., 2023), widespread declines in deepwater oxygen during summer stratification have emerged as a growing concern for many lakes worldwide (Jane et al., 2021, 2022; Jansen et al., 2024). Stratification occurs in lakes when water density differences between surface and bottom waters create a

layered structure in the water column, inhibiting vertical mixing (Boehrer and Schultze, 2008). In this state, the deepwater (hypolimnion) is isolated from the upper mixed layer (epilimnion) restricting access to atmospheric oxygen exchange and photosynthesis, causing oxygen to be steadily consumed by microbial respiration and sedimentary processes (Livingstone and Imboden, 1996; Schwefel et al., 2018). Prolonged deepwater hypoxia (DO < 2 mg L⁻¹ O₂) or anoxia (DO < 0.5 mg L⁻¹ O₂) severely impact aquatic ecosystems, leading to habitat loss for fish species (Jones et al., 2008; Kraus et al., 2023; North et al., 2014) and native invertebrate populations (Galic et al., 2019). Understanding how DO may change in the future is crucial to conserve lake ecosystem

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<https://doi.org/10.1016/j.envsoft.2026.106941>

Received 9 September 2025; Received in revised form 15 January 2026; Accepted 3 March 2026

Available online 5 March 2026

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services.

Deepwater oxygen dynamics in lakes are governed by complex interactions between physical and biogeochemical processes (Marcé et al., 2023). Mineralisation of organic matter drives the most important biogeochemical oxygen demand from the water column and sediments in freshwaters (Livingstone and Imboden, 1996; Schwefel et al., 2018). Eutrophication intensifies oxygen depletion by promoting primary production and ecosystem respiration (Burns, 1995; Cornett and Rigler, 1987; Matzinger et al., 2010; Pace and Prairie, 2005; Rippey and McSorley, 2009; Walker, 1979). Nevertheless, internal physical mechanisms also play a crucial role in regulating hypolimnetic oxygen dynamics across diverse lake systems (Jane et al., 2021; Jansen et al., 2024). These physical dynamics are governed by four temperature-related factors: stratification duration, stratification onset temperature, average bottom temperature and deepwater mixing. First, longer stratification caused by earlier onset and later turnover dates would prolong the duration of oxygen depletion (Fang and Stefan, 2009; Foley et al., 2012; Rippey and McSorley, 2009). Second, higher temperatures at stratification onset, defined as when deepwater is almost fully oxygen-saturated, leads to reduced oxygen solubility (Livingstone and Imboden, 1996; Mortimer, 1981). Third, deepwater warming during stratification accelerates microbial metabolism, resulting in faster rates of respiration and decomposition (Gudas et al., 2010). Finally, reduced diffusivity coefficient, which links to stronger thermal gradients slows oxygen transfer into deepwater (Jassby and Powell, 1975; Kreling et al., 2017). Many lake models have projected longer stratification and warmer bottom waters during stratified periods under future climate scenarios (Ayala et al., 2020; Butcher et al., 2015; Jansen et al., 2022; Sahoo et al., 2016; Shatwell et al., 2019; Tan et al., 2018; Woolway et al., 2022), but less attention has been given to changes in onset temperature and deepwater mixing coefficient.

Coupled hydrodynamic-biogeochemical models have commonly projected declines in deepwater oxygen concentrations under future climate warming (Jiménez-Navarro et al., 2023; Tan et al., 2018; Yaghouti et al., 2023), yet a mechanistic analysis of the underlying physical drivers remains scarce. In addition, these models typically require extensive datasets and are subject to large parameter uncertainties, which constrains their broader applicability. A simple, data-efficient model that can both enhance mechanistic understanding and support climate-adaptive lake management has been largely overlooked.

The aim of this study was to develop a simple and deductive 1-D oxygen model that requires readily available data with broad lake-system applications. This modelling tool enabled us to address three questions: (1) how will climate change affect deepwater oxygen dynamics in the future, based on present-day oxygen depletion rates? (2) which physical factors contribute most to changes in oxygen dynamics? and (3) what reduction in present-day oxygen depletion rates is required to offset climate impacts and maintain stable deepwater oxygen levels through 2100? To offset the possible influence of climate change, one of the potentially effective measures is reducing the oxygen depletion rates, which could be achieved through nutrient reductions (Müller et al., 2014; Schindler, 2006; Schwefel et al., 2024). Ensuring stable deepwater oxygen levels is essential for safeguarding ecosystem functioning and resilience in the face of ongoing climate change (Carey, 2023; Rhodes et al., 2017; Rose et al., 2024).

We established a vertical deepwater oxygen model that simulates deepwater oxygen profiles during the summer stratified period. The model incorporates oxygen uptake from both the sediment and the water column, which are linked to lake productivity, as well as vertical oxygen mixing. Following validation using measured data from Lake Erken, Sweden, the model was driven by water temperature and diffusivity profiles from a 1-D hydrodynamic model (Ayala et al., 2020) to project the deepwater DO under historical and future climate scenarios. We then identified the most important physical drivers of oxygen loss. Finally, we simulated multiple DO depletion scenarios to estimate the

reduction in oxygen demand required to offset the effects of climate change and maintain 2020s oxygen levels by the end of the century.

2. Method

2.1. Study site

Lake Erken has been the focus of multiple modelling studies (Ayala et al., 2020; Hamilton et al., 2015; Jiménez-Navarro et al., 2023; Moras et al., 2019; Yang et al., 2016). It is a moderately deep lake with a retention time of approximately 7 years, located in east-central Sweden (59°51' N, 18°36' E) at an altitude of 10 m above sea level. Erken has an average depth of 9 m, maximum depth of 21 m and surface area of 24 km² (Weyhenmeyer et al., 1995). This mesotrophic lake is located in a relatively small (141 km²) forested catchment, where human activity is limited to low-intensity farming (Malmaeus et al., 2006). It is classified as a dimictic lake, with summer stratification from May-June to August-September, ice-on from December to February and ice-off from March to April (Persson and Jones, 2008).

2.2. Data sets

From 2019 to 2022, hourly temperature and DO profiles were recorded by a YSI EXO2 sonde on an automated profiling system located near the deepest point of the lake (59.84065° N, 18.627767° E; SITES, 2024). Water temperature was measured using an EXO Conductivity & Temperature sensor with an accuracy of ± 0.01 °C, while DO was recorded via an EXO Optical Dissolved Oxygen Digital Smart Sensor with an accuracy of ± 0.1 mg L⁻¹ (SITES, 2024). An automated wiping system was employed to prevent biofouling of the oxygen sensor. The vertical profiles were recorded at 0.5 m intervals between 1 and 17 m depth (Fig. S1; see Section S1 in the SI for measurement pre-processing). Daily aggregated temperature and oxygen profiles from 2019 to 2020 were used for model setup and validation. Weekly in-situ oxygen profile measurements, collected at the deepest point of the lake between 1996 and 2005 (SITES, 2024) were also used to evaluate the historical simulations.

2.3. Dissolved oxygen model structure

A one-dimensional deductive model was developed to simulate the hypolimnion DO profiles during the stratified period. The model was driven by temperature and vertical diffusivity (K_z) profiles, lake bathymetry and two parameters: water-column oxygen depletion rate (J_V) and sediment oxygen depletion rate (J_A). The division of hypolimnetic oxygen consumers into sediment and the water column components follows the approach of Livingstone and Imboden (1996). Both oxygen demands are adjusted by a temperature-dependent multiplier (K_{temp}). To account for vertical oxygen mixing, diffusive fluxes into and throughout the hypolimnion layers were included in the model. Temperature data can also be used to estimate K_z profiles based on the heat budget method (see Section S2 in the SI).

Oxygen concentrations were investigated in deepwater layers (Fig. 1), based on pre-defined fixed depths similar to previous studies (Nkwale et al., 2024; North et al., 2014; Weber et al., 2017). The upper boundary of deepwater in Erken was defined at a depth of 13.75 m from the surface. This depth was well below the euphotic zone in Erken (5.7–9.7 m from the surface; Istvanovics et al., 1994) and would be isolated from oxygen sources (Bell and Kuparinen, 1984). The upper boundary of the mixed layer occasionally deepens beyond 13.75 m during the stratified period (based on 2019–2022 observations); consequently, the fixed deepwater region defined in our model largely overlapped with the hypolimnion (Fig. S2; see Section S3 in the SI).

A coupled set of differential equations was solved for the mass balance of DO in each layer of the deepwater during the stratified period. The backward Euler (implicit) integration strategy was used for the

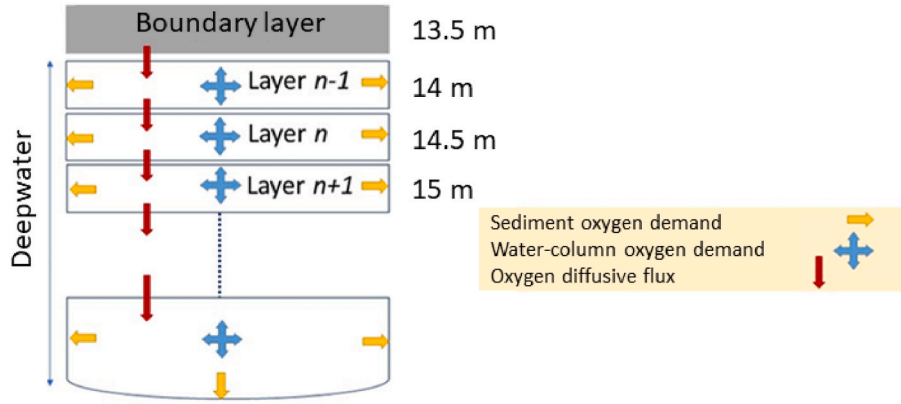


Fig. 1. Conceptual configuration of the deepwater DO model for Erken.

numerical solution on a daily time step (Hutter et al., 2010). The mass balance equation for the n th segment (positive downward- Fig. 1) is shown in Eqs. (1)–(3).

$$\frac{\Delta C_n}{\Delta t} = \frac{A_n}{V_n \Delta z_n} K_{z,n} (C_{n-1} - C_n) + \frac{A_{n+1}}{V_n \Delta z_n} K_{z,n+1} (C_{n+1} - C_n) - J_n^{mod} \quad (1)$$

$$J_n^{mod} = K_{temp,n} (J_V + J_A \alpha_n) \quad (2)$$

$$K_{temp,n} = \theta^{T_n - 20} \quad (3)$$

where.

C_n DO concentration in layer n [mg L^{-1}]

A_n Surface area of the upper boundary of layer n [m^2]

V_n Volume of layer n [m^3]

Δz_n Thickness of layer n [m]

$K_{z,n}$ Diffusivity coefficient at the upper boundary of layer n [$\text{m}^2 \text{s}^{-1}$]

$K_{temp,n}$ Temperature correction coefficient of oxygen depletion rates in layer n [-]

J_n^{mod} DO depletion rate corrected by temperature coefficient in layer n [$\text{g m}^{-3} \text{d}^{-1}$]

θ The temperature multiplier with a value of 1.087 [-] (Gudas et al., 2010)

T_n Average temperature in layer n [$^{\circ}\text{C}$]

J_V Oxygen depletion rate of the water column in layer n [$\text{g m}^{-3} \text{d}^{-1}$] at 20°C

J_A Sediment-related oxygen depletion rate in layer n [$\text{g m}^{-2} \text{d}^{-1}$] at 20°C

α_n Morphometric function ($\frac{A_n}{V_n}$) as the ratio of sediment area to water volume in layer n [m^{-1}].

In Eq. (1), the term $\frac{A_n}{V_n \Delta z_n} K_{z,n} (C_{n-1} - C_n)$ is the DO diffusive flux entering layer n from the overlying layer ($n-1$) and $\frac{A_{n+1}}{V_n \Delta z_n} K_{z,n+1} (C_{n+1} - C_n)$ is the DO diffusive flux that goes from layer n into the below layer ($n+1$) (Fig. 1), which was set to 0 for the deepest layer. The diffusivity coefficient, $K_{z,n}$, can be computed as a time-dependent parameter from temperature profiles using SE1 in the SI (Heinz et al., 1990; Jassby and Powell, 1975).

The model defines the initial condition on the day before stratification begins, hereafter called the stratification onset. In dimictic years in which the lake stratifies once in summer and remains stratified continuously until autumn overturn, the onset deepwater DO concentration is assumed to be fully saturated, determined by water temperature only (Mortimer, 1981; see Section S4 in the SI). Otherwise, summer stratification is broken into several discontinuous periods by mid-summer mixings, which are defined as polymictic years. Following a

mid-summer mixing event in a polymictic year, the DO saturation level at the onset of stratification was estimated using an empirically derived replenishment rate rather than assuming full temperature-based saturation. The rate (2.79% DO saturation per day) was calculated from deepwater observations during an 11-day partial mixing period in 2019 (Jun 30–Jul 10; Fig. S3). The rate was multiplied by the number of mid-summer mixing days in each polymictic year to estimate the increase in DO saturation and then added to the DO level at the end of the previous stratification period. In climate scenario simulations, this empirical rate was applied for years with mid-summer mixing, which represented a minor fraction of total simulation years (See Section S5 in the SI).

The solution of Eq. (1) also requires DO values in the boundary layer (13.5 m in Fig. 1) to estimate the oxygen mixing flux into deepwater. In Erken, boundary-layer oxygen concentrations declined linearly throughout the stratified period (Fig. S4 in the SI), following Livingstone and Imboden (1996). Therefore, the oxygen concentration in the boundary layer was modelled by a linear function with an oxygen depletion rate of $0.366 \text{ g m}^{-3} \text{d}^{-1}$ adjusted by a temperature-dependent multiplier (see Section S6 in the SI).

2.4. Model setup

2.4.1. Stratification period

Oxygen depletion of deepwater in Erken typically starts after the onset of summer stratification and lasts until the water column overturns in Autumn (Jiménez-Navarro et al., 2023). Deoxygenation occurs only after a prolonged stratification period, thus short periods of ephemeral stratification that occasionally appear outside of the main summer stratification are not considered in this study. Summertime was defined as when surface water temperature was warmer than 4°C , which is indicative of stratified conditions (Boehrer and Schultze, 2008). This main deoxygenation period was defined using DO measurements from 2019 to 2022. The start of the deoxygenation period was defined as the day of year when the deepwater volume-weighted average oxygen saturation first decreased below 100% and continued to decline for a minimum of a further six days (grey squares in Fig. 2). The end of deoxygenation is defined as the first day within a 7-day period during which the total increase in oxygen saturation is at least 10 % (grey triangles in Fig. 2). This definition removed the ephemeral periods of stratification and captured well the observed onset and end of deoxygenation during 2019 to 2022 (Fig. 2).

The stratification duration for the oxygen model was identified using water temperature profiles that coincided with deoxygenation duration. The stratification period was defined according to a density difference (calculated from a temperature profile data; Imberger and Patterson, 1989) between the boundary layer (the layer above deepwater; see Fig. 1) and the surface of greater than 0.05 kg m^{-3} (a common threshold;

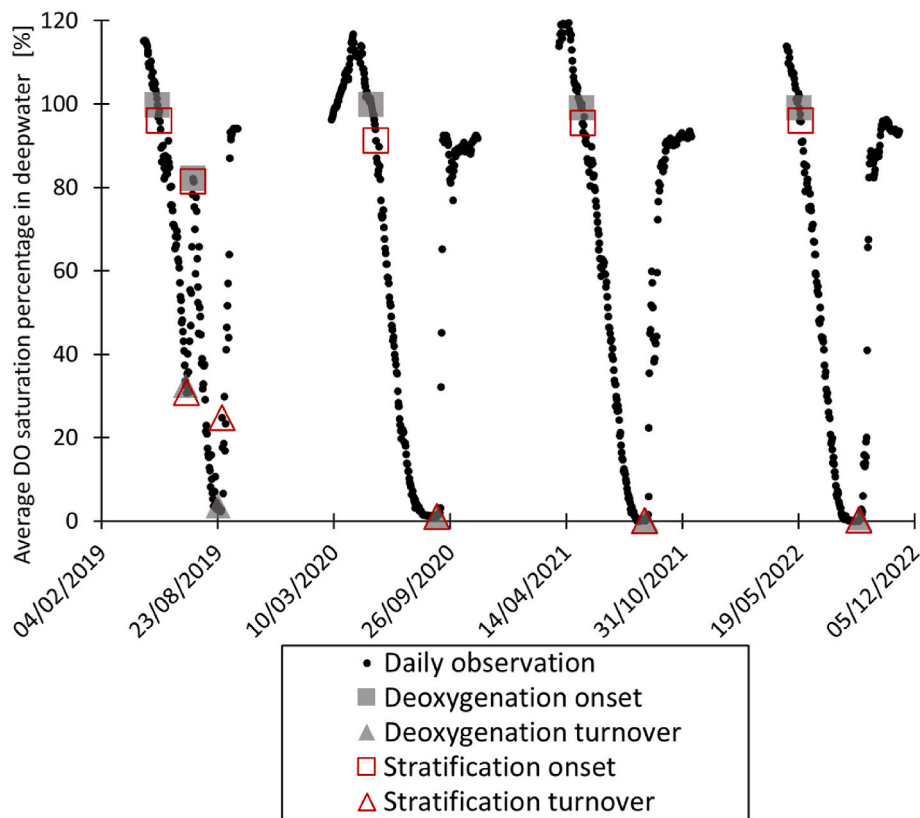


Fig. 2. Deepwater deoxygenation and stratification periods from 2019 to 2022.

Wilson et al., 2020) for at least 7 days (red square and red triangle in Fig. 2). This stratification period aligned well with the deoxygenation period defined above from the observed oxygen profiles, with a MAE (Mean Absolute Error; SE7 in the SI) of 5 days across the years 2019 to 2022 (Fig. 2). For future projections, we assumed that the defined stratified period would reasonably coincide with the deoxygenation period in the deepwater.

2.4.2. Optimisation of model parameters

The two parameters for the model, water-column oxygen depletion rate (J_V) and sediment oxygen depletion rate (J_A), were optimised based on oxygen profiles collected in 2020 and 2021. The lower bounds for these parameters were set at $0.01 \text{ g m}^{-3} \text{ d}^{-1}$ for J_V and $0.01 \text{ g m}^{-2} \text{ d}^{-1}$ for

J_A (Lardner-Cornett, 1982; Nkwale et al., 2024). The upper bounds of J_V ($0.85 \text{ g m}^{-3} \text{ d}^{-1}$; Nkwale et al., 2024) and J_A ($1.7 \text{ g m}^{-2} \text{ d}^{-1}$; Tasnim et al., 2021) were adopted based on maximum values for mesotrophic lakes at a reference temperature of 20°C . A total of 180 parameter sets were generated using grid sampling with uniform step sizes of $0.1 \text{ g m}^{-3} \text{ d}^{-1}$ (J_V) and $0.1 \text{ g m}^{-2} \text{ d}^{-1}$ (J_A). This sampling approach has previously been applied to optimise oxygen depletion parameters (Weber et al., 2017).

To account for parameter uncertainty, the Generalized Likelihood Uncertainty Estimation (GLUE) approach (Beven and Binley, 1992) was applied, following the equifinality principle. Out of 180 tested parameter sets, 30 were deemed acceptable with a Root Mean Square Error (RMSE; SE8 in the SI) below 0.75 mg L^{-1} in DO profile simulations and

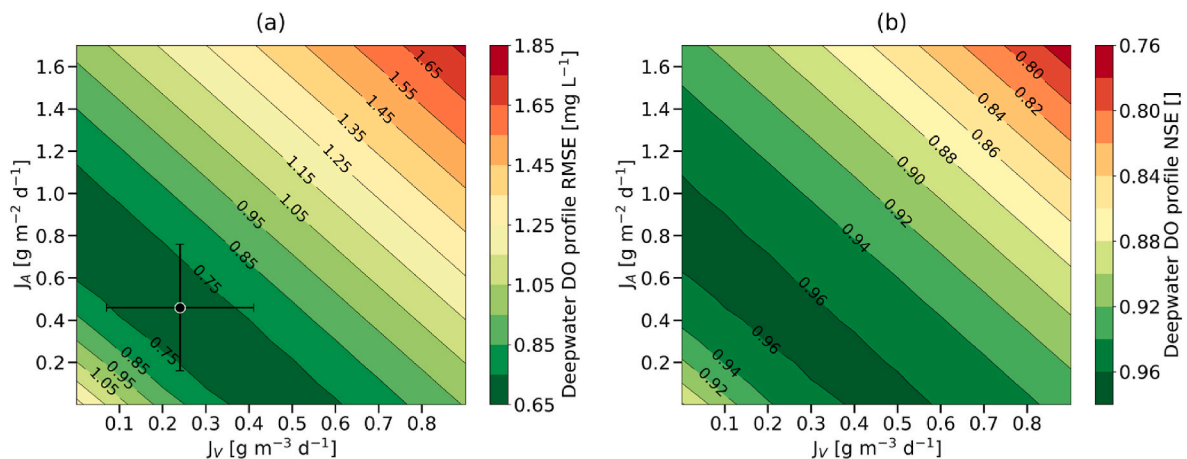


Fig. 3. Optimisation of deepwater DO model parameters (J_A and J_V) based on (a) RMSE and (b) NSE in 2020 and 2021. The black marker in panel (a) indicates the mean acceptable parameter sets ($\text{RMSE} < 0.75 \text{ mg L}^{-1}$), with error bars representing ± 1 standard deviation.

J_V of $0.24 \pm 0.17 \text{ g m}^{-3} \text{ d}^{-1}$ (mean $\pm$ standard deviation) and J_A of $0.46 \pm 0.3 \text{ g m}^{-2} \text{ d}^{-1}$ (within the dark green area in Fig. 3a). Each accepted parameter set was assigned a likelihood value derived from its Nash–Sutcliffe Efficiency (NSE; SE9 in the SI) with an average of 0.96 ± 0.002 across the acceptable parameter sets (Fig. 3b). NSE, which is commonly used as a likelihood measure in GLUE applications (Nkonge et al., 2014), was normalised so that all likelihoods summed to one. These relative probability weights were assigned to each accepted parameter set. These weights were then used to rank the corresponding model projections in ascending order. Finally, weighted quantiles (5th, 50th and 95th percentiles) were calculated from the cumulative weighted distribution of the ranked model projections, providing the median as well as the lower and upper bounds of the 90% confidence interval (CI).

Using the 30 parameter sets, the simulated average deepwater DO in 2020 and 2021 closely matched observations with an RMSE of $0.69 \pm 0.02 \text{ mg L}^{-1}$ and an NSE of 0.96 ± 0.02 (Fig. 4a and b). The model was also validated under different mixing regimes since a small number of future years experienced polymictic conditions. The model showed reasonable agreement in estimating daily average deepwater oxygen, with an RMSE of $1.70 \pm 0.28 \text{ mg L}^{-1}$ and an NSE of 0.75 ± 0.08 in a polymictic year (2019; Fig. 4c) and an RMSE of $1.06 \pm 0.12 \text{ mg L}^{-1}$ and an NSE of 0.91 ± 0.02 in a dimictic year (2022; Fig. 4d). It also reasonably reproduced deepwater oxygen profiles (Fig. S5 in the SI). Despite above-average wind speeds in 2019 compared to the long-term historical average (SITES, 2024), the DO model performed reasonably well, indicating that it can also regenerate the deepwater DO profile under weak mixing conditions.

2.5. Oxygen under climate scenarios

The daily water temperature profiles and vertical diffusivity coefficients under historical and future emission scenarios were obtained

from the 1-D hydrodynamic model, GOTM (General Ocean Turbulence Model; Umlauf et al., 2005), which previously applied to Lake Erken (Ayala et al., 2020). These GOTM outputs were then driven into our oxygen model using the 30 acceptable parameter sets, forming the GOTM–DO coupled modelling framework in this study. The GOTM daily diffusivity (average: $7.8 \times 10^{-6} \text{ m}^2 \text{ s}^{-1}$) showed reasonable agreement with those calculated from the measured fortnightly temperature profiles using the heat budget method (average: $1.1 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$) in 2020–2021. Deepwater DO profiles were simulated using the GOTM-coupled DO model for the historical period (1861–2005) and under three Representative Concentration Pathways (RCP2.6, RCP6.0 and RCP8.5) for 2006–2099. Simulations for each scenario were driven by four General Circulation Models (GCMs): GFDL-ESM2M, HadG-EM2-ES, IPSL-CM5A-LR and MIROC5, provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b; Frieler et al., 2017).

Several oxygen metrics were used to quantify the impacts of climate change on simulated deepwater oxygen profiles. Firstly, the volume-weighted average deepwater DO concentration in July and August was calculated each year, as Erken is typically stratified during these two months (Persson and Jones, 2008). Since DO concentrations vary with depth, using a volume-weighted average provides a more representative measure of the overall oxygen content in the deepwater (Quinlan et al., 2005). Secondly, the annual anoxic and hypoxic factors were calculated (Nürnberg, 1995) representing the sum of daily sediment areas experiencing deepwater anoxic ($<0.5 \text{ mg L}^{-1}$) or hypoxic ($<2 \text{ mg L}^{-1}$) conditions, normalised by the lake surface area (see Section S9 in the SI). Thirdly, the total number of days in which the entire deepwater profile was anoxic (deepwater anoxia duration) was calculated annually.

Changes in thermal stratification and oxygen conditions were tracked from the historical to the future climatic scenarios. The Mann-Kendall test for independent data and its modified version for autocorrelated data (Hamed and Rao, 1998), were applied to identify monotonic trends at a significance level of 0.05 (Gilbert, 1987; Kendall, 1948; Mann, 1945) in 2020–2099. Sen's slope was then used to quantify slopes and intercepts of significant trendlines (Hipel and McLeod, 1994; Sen, 1968).

2.6. Sources of uncertainty

The analysis of variance (ANOVA; Feldbauer et al., 2022) was used to quantify how two sources of uncertainty, GCM selection and model parameter sets, contributed to projected oxygen metrics under climate scenarios. ANOVA was applied to each metric to estimate the contributions of these sources and their interactions.

2.7. Attribution

We performed separate Random Forest (RF) regression analyses for each of the four DO metrics to identify key temperature-related driver(s) of summer deepwater deoxygenation. RF models are based on an ensemble of decision trees (Breiman, 2001). Regression tree models are suitable for capturing non-linear relationships, multicollinearity and interactions among model drivers (De'ath & Fabricius, 2000). In this study, regression trees were developed in Python using the scikit-learn package (Pedregosa et al., 2011). Predictor variables were derived from the annual ensemble medians of the GCMs under the historical scenario (1861–2005), including: (1) stratification duration, (2) bottom (boundary layer and deepwater; see Fig. 1) DO at stratification onset based on onset temperature-determined saturation, (3) temperature correction coefficient for oxygen depletion rates (K_{temp}) based on average bottom temperature and (4) diffusivity coefficient (K_z) at top layer of the deepwater. The simulated annual median oxygen metrics from 1861 to 1947 (60%) were used for training, while data from 1948 to 2005 (40%) were used for testing. RF models were built with 1000 trees and were tuned using grid search with 10-fold cross-validation to minimise training RMSE (Genuer et al., 2010; Probst et al., 2019). To

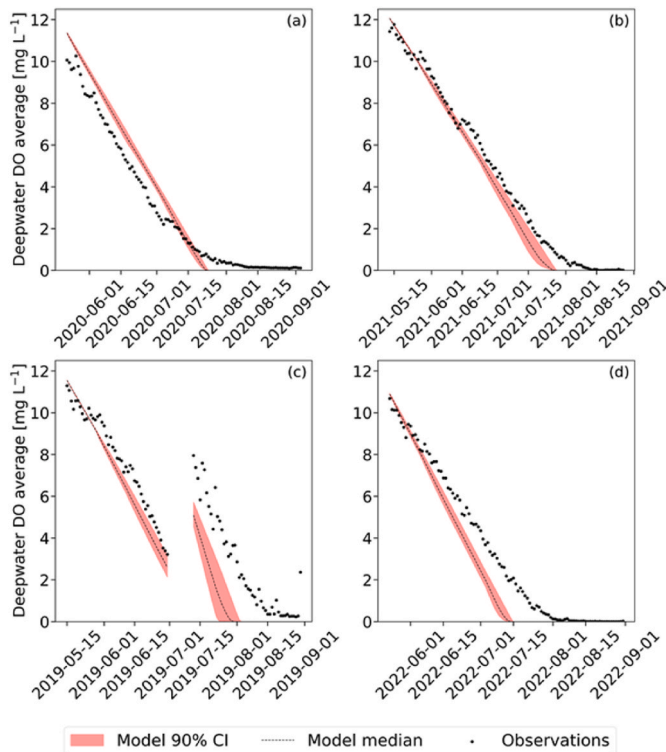


Fig. 4. Daily average of deepwater DO from 2019 to 2022. The dimictic years (a, b and d) showed continuous summer stratification, whereas the polymictic year (c) experienced a mid-summer mixing event.

avoid overfitting, the permutation importance was calculated as the increase in test-set RMSE after randomly shuffling each predictor (Breiman, 2001). We also evaluated the performance of the RF model and our oxygen model by comparing their RMSEs against observed Jul–Aug deepwater DO in 1996–2005. Changes in temperature-dependent factors were also tracked over the last 80 years of this century.

2.8. Target volume-related hypolimnetic oxygen depletion rate

Sediment and water-column oxygen depletion rates can be combined to form a volume-related hypolimnetic oxygen depletion rate (VHOD) (Livingstone and Imboden, 1996) using a morphometrical ratio (Eq. (4)). Hypolimnetic bulk morphometrical ratio (α_b) -the ratio of the sediment area to the water volume (Livingstone and Imboden, 1996)- in Erken deepwater is 0.48 m^{-1} . The current VHOD based on model parameters optimisation was estimated at $0.46 (\pm 0.08) \text{ g m}^{-3} \text{ d}^{-1}$ from the average of 30 acceptable sets of J_V and J_A .

$$\text{VHOD} = J_V + \alpha_b J_A \quad (4)$$

If climate-driven changes in thermal structure increase deoxygenation in the future, preserving present-day deepwater oxygen levels would require a reduction in VHOD. To estimate the extent of VHOD reduction, the model was run with different VHOD values between 0.01 and 0.60 (the maximum VHOD with $\text{RMSE} < 0.75 \text{ mg L}^{-1}$) at intervals of $0.01 \text{ g m}^{-3} \text{ d}^{-1}$. The boundary layer oxygen depletion rate ($0.366 \text{ g m}^{-3} \text{ d}^{-1}$) was also scaled based on the ratio of each VHOD value to current VHOD ($0.46 \text{ g m}^{-3} \text{ d}^{-1}$). Average model projections in two decades, the 2020s (2020–2029) and the 2090s (2090–2099), were used to determine present and future oxygen conditions. The target VHOD was defined as the VHOD value that makes the 2090s oxygen metrics equal to those projected for the 2020s. The difference between the target VHOD and $0.46 \text{ g m}^{-3} \text{ d}^{-1}$ quantify the required mitigation to maintain oxygen stability under each emissions pathway.

3. Results

3.1. Stratification and DO changes under climate scenarios

Our simulations suggest that stratification will begin 8–10 days (the quoted range represents results under different RCPs) earlier in the near future (2030–2059) and 11–20 days earlier in the distant future (2070–2099) in Lake Erken, relative to the baseline period (1976–2005) (Table 1). This shift resulted in longer stratification by 11–13 days in the near future and 15–31 days in the distant future. The greatest shifts in stratification pattern and oxygen metrics occurred under RCP8.5. Under

all future scenarios (both near and distant), the average deepwater DO for Jul–Aug remained below 0.5 mg L^{-1} . Jul–Aug oxygen levels decreased by 62–71% in the near future and 65–97% in the distant future compared to the baseline (Table 1). Both annual anoxic (Table 1) and hypoxic (Table S1 in the SI) factors are projected to increase by up to 2 days in the near future and 5 days in the distant future. The deepwater hypoxic factors and anoxia duration under RCP8.5 are projected to increase by 76% and 97%, respectively, by the end of the century (Table S1 in the SI).

From 2020 to 2099, deepwater DO in Jul–Aug decreased significantly under RCP6.0 and RCP8.5, both with a trend of $-0.1 \text{ mg L}^{-1} \text{ decade}^{-1}$ (p-value < 0.001 ; Fig. 5a). Both anoxic and hypoxic factors increased under RCP6.0 and more sharply under RCP8.5, with rates of 0.4 and $0.6 \text{ d year}^{-1} \text{ decade}^{-1}$, respectively (Fig. 5b; Fig. S6a in the SI). Anoxia duration in deepwater extended by 3 d decade^{-1} under RCP6.0 and more rapidly by 5 d decade^{-1} under RCP8.5 (Fig. S6b in the SI). No significant trends were found under RCP2.6 for any oxygen metrics (Fig. 5; Fig. S6 in the SI).

Most of the uncertainty in projected oxygen metrics was attributed to GCMs ($> 96\%$), whereas the contribution of parameter selection was minor ($< 4\%$). Interactions between these two sources accounted for less than 1% of the total variance (See S11 in the SI for details). The limited influence of parameter selection reflects that the 30 accepted parameter sets produced very similar model performance and narrow range of likelihood values (Fig. 3).

3.2. Attribution test results

The importance of four temperature-related DO factors from GOTM was assessed based on the RF model's ability to reproduce oxygen metrics that were simulated by the GOTM-coupled DO model. The RF model estimated Jul–Aug deepwater DO with an RMSE of $0.50 \pm 0.17 \text{ mg L}^{-1}$ for the training set and 0.49 mg L^{-1} for the test set (Fig. 6). Both the RF and oxygen models showed acceptable performance, with RMSEs of 2.54 mg L^{-1} and 2.35 mg L^{-1} , respectively, compared to observations from Jul–Aug 1996–2005. Permutation importance analysis of all oxygen metrics identified stratification duration as the primary driver of deepwater oxygen dynamics during the stratified period (Fig. 6 and Fig. S7 in the SI). This indicates that longer stratification duration, by an average of 8–37 days under RCPs 2.6–8.5, would mainly regulate future deoxygenation in 2020–2099 (Fig. S8a in the SI). A slight bottom warming under RCP8.5 ($0.07 \text{ }^\circ\text{C per decade}$) (Fig. S8d in the SI) may further accelerate deoxygenation by increasing oxygen consumption rates. In contrast, the decreasing trend in onset temperature under RCP2.6 ($-0.11 \text{ }^\circ\text{C per decade}$) (Fig. S8b in the SI) is expected to slightly weaken future deoxygenation. Variations in bottom-water onset

Table 1

Changes in deepwater stratification patterns and oxygen during the baseline (1976–2005), near future (2030–2059) and distant future (2070–2099) under different emission scenarios. The values represent as the average projection $\pm$ standard deviation (% change from the baseline average).

	Baseline	RCP2.6	RCP6.0	RCP8.5
Onset day [DOY]	132.0 ± 0.9	Near future 122.6 ± 10.4 (−7%) Distant future 121.3 ± 9.8 (−8%)	123.7 ± 9.6 (−6%) 117.4 ± 11.9 (−11%)	121.5 ± 11.6 (−8%) 112.6 ± 11.7 (−15%)
Stratification duration [d]	112.2 ± 5.4	Near future 125.1 ± 14.7 (−11%) Distant future 127.1 ± 3.9 (−13%)	123.0 ± 14.9 (−10%) 135.5 ± 7.7 (−21%)	125.6 ± 0.3 (−12%) 143.4 ± 0.9 (−28%)
DO in Jul–Aug [mg L^{-1}]	1.29 ± 0.66	Near future 0.47 ± 0.50 (−64%) Distant future 0.45 ± 0.43 (−65%)	0.49 ± 0.52 (−62%) 0.13 ± 0.29 (−90%)	0.38 ± 0.84 (−71%) 0.04 ± 0.34 (−97%)
Anoxic factor [d year^{-1}]	5.68 ± 1.05	Near future 7.57 ± 1.20 (−33%) Distant future 7.67 ± 1.14 (−35%)	7.46 ± 1.25 (−31%) 9.37 ± 1.41 (−65%)	8.22 ± 1.69 (−45%) 10.91 ± 1.82 (−92%)

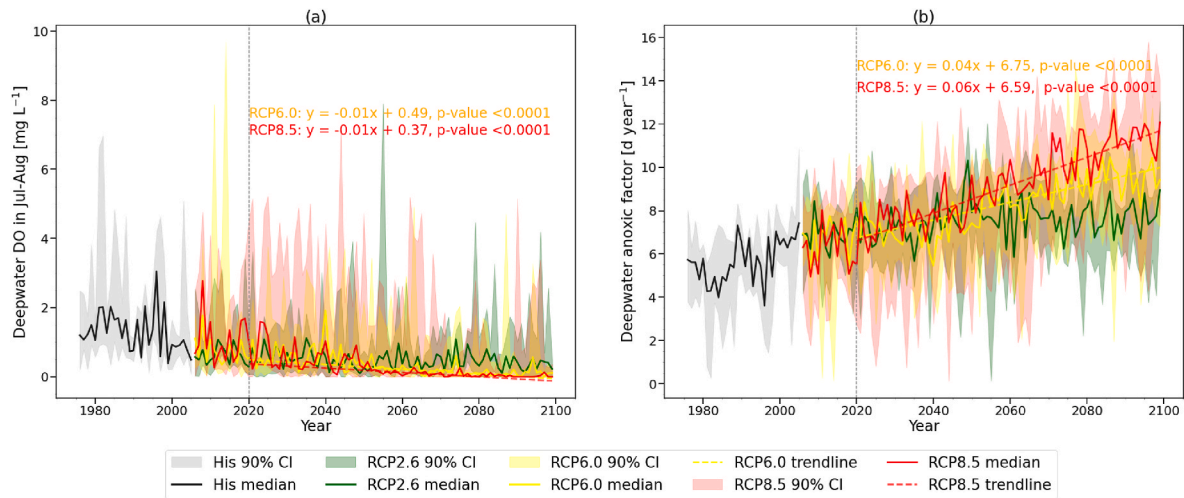


Fig. 5. Deepwater (a) DO average in Jul-Aug and (b) annual anoxic factor, simulated with 4 GCMs and 30 parameter sets. Trendlines for 2020–2099 are shown if the Mann-Kendall test p-value is < 0.05 .

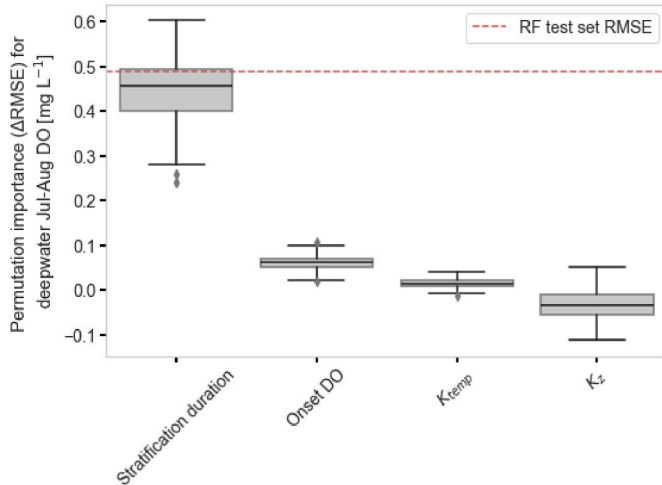


Fig. 6. Importance of climate-related DO factors and the RF performance in projecting Jul-Aug deepwater DO in the test period (1948–2005).

temperature reflect heat transfer from the surface during the transition

between the spring isothermal period ($\sim 4^\circ\text{C}$) and the onset of stratification (identified based on density difference; see 2.4.1). The magnitude of this heat transfer depends on the balance between earlier stratification onset and external climate forcing, resulting in no significant trend in onset temperature under RCP6.0 and RCP8.5.

3.3. Depletion rate management

Using the current VHOD ($0.46\text{ g m}^{-3}\text{ d}^{-1}$), the model projected an anoxic factor of 6.74, 6.93 and 7.52 d year^{-1} for the 2020s under RCP2.6, RCP6.0 and RCP8.5, respectively (Fig. 7). If VHOD remains unchanged, the anoxic factor was estimated to increase to 7.94 (RCP2.6), 9.50 (RCP6.0) and 11.44 (RCP8.5) d year^{-1} in the 2090s. To offset this climate-induced deoxygenation and maintain the 2020s anoxic factor levels by the end of the century, VHOD would require reductions to 0.40 (RCP2.6), 0.35 (RCP6.0) and 0.32 (RCP8.5) $\text{g m}^{-3}\text{ d}^{-1}$, respectively (Fig. 7). These target VHODs represent reductions of 13% (RCP2.6), 24% (RCP6.0) and 30% (RCP8.5) relative to the current VHOD. This reductions were also sufficient to stabilise annual deepwater anoxia duration (Fig. S9 in the SI). When evaluated using the hypoxic factor, similar reductions were sufficient under RCP2.6 and RCP6.0; however, under the extreme RCP8.5 scenario the system was more sensitive, requiring a larger VHOD reduction of 35% (Fig. S10 in

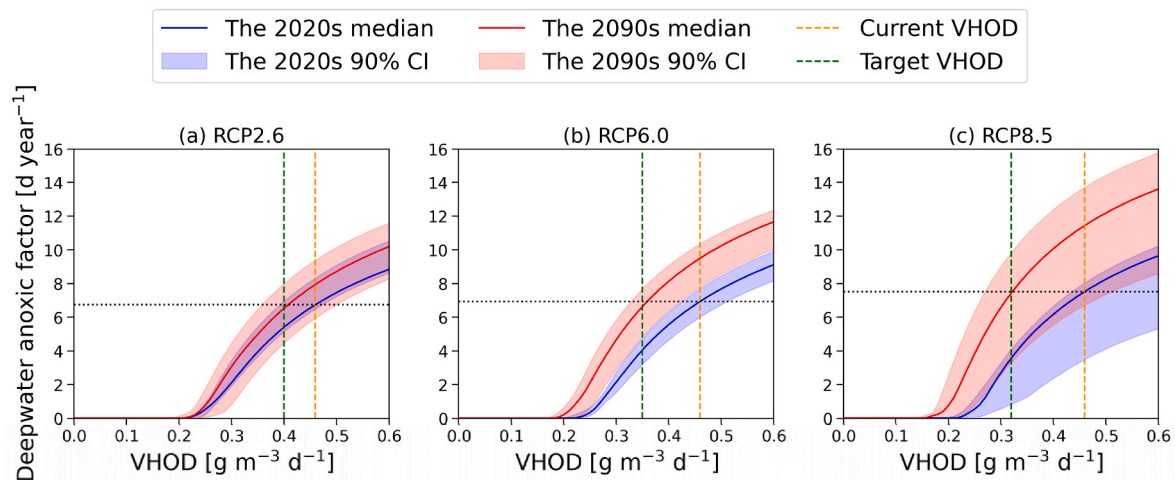


Fig. 7. Target VHOD for maintaining the 2020s annual anoxic factor (horizontal dotted line) in the 2090s under (a) RCP2.6, (b) RCP6.0 and (c) RCP8.5, resulting from a total of 120 simulations.

the SI). In contrast, maintaining the deepwater DO average in Jul–Aug would require smaller VHOD reductions of 9%, 20% and 26% under RCP2.6, RCP6.0 and RCP8.5, respectively (Fig. S11 in the SI).

4. Discussion

In this study, we developed a simple deepwater DO profile model and applied it to Lake Erken. Using several oxygen metrics, our projections indicate substantial deepwater oxygen decline by the end of the century, particularly under high-emission scenarios. For example, the duration of deepwater anoxia is projected to increase by approximately 1.5-fold under RCP6.0 and 1.8-fold under RCP8.5 from 2020 to 2100. Oxygen loss is less pronounced under RCP2.6. This modelling framework provides a novel and computationally efficient tool for exploring future trajectories of oxygen dynamics and supporting mechanistic analyses. We demonstrate that future climate-driven deepwater deoxygenation in a temperate lake is primarily caused by extended summer stratification. This modelling framework also quantifies the scale of interventions required to mitigate future climate impacts by estimating necessary changes in the deepwater oxygen depletion rate. These estimates provide a physically-driven baseline, as they account for climate-induced shifts in thermal and stratification phenology but assume that present-day biogeochemical processes remain constant. Accordingly, maintaining current oxygen conditions by the end of the century in Erken would require reductions in DO depletion rate of up to 24% and 35% under RCP6.0 and RCP8.5, respectively. In contrast, more moderate interventions of up to 13% would be sufficient to mitigate climate-driven deoxygenation under RCP2.6.

Our projected decline in deepwater DO by the end of the century is broadly consistent with earlier estimates for Lake Erken (Jiménez-Navarro et al., 2023), even if the absolute magnitude is slightly lower. This minor discrepancy appears linked to assumptions regarding nutrient loading, highlighting that climate-driven oxygen loss can be exacerbated by ongoing eutrophication. Furthermore, our results fall within the range reported for other northern temperate lakes (e.g., German and Canadian systems), supporting that climate-driven stratification changes are emerging as a regional-scale driver (Schwefel et al., 2024; Tan et al., 2018; Yaghouti et al., 2023). Lake Erken is projected to experience a ~30% increase in stratification duration by 2100 under RCP8.5, a shift that aligns closely with the median projection for northern temperate lakes (Woolway et al., 2021). This decisive role of stratification phenology in driving deepwater deoxygenation is well-supported by historical evidence (Foley et al., 2012; Jane et al., 2021, 2022; Jansen et al., 2024; North et al., 2014; Rippey and McSorley, 2009) and reinforced by climate projections that consistently indicate further lengthening of stratification periods at the global scale (Huang et al., 2024; Nikoo et al., 2025; Schwefel et al., 2024; Sharma et al., 2019; Woolway et al., 2021). Apart from climate warming, other anthropogenic pressures such as atmospheric stilling (Woolway et al., 2017, 2019) and browning (Knoll et al., 2018; Pilla et al., 2018, 2020; Williamson et al., 2015) can further prolong stratification. Therefore, we expect that deepwater oxygen loss is likely to become a major global challenge by the end of the 21st century.

As data scarcity limits the application of many lake modelling tools (Mooij et al., 2010), our model is intentionally designed for simplicity and transferability. It requires only bathymetry, daily temperature and DO profiles. By minimising input data and computational demands, the model is particularly well-suited for large-scale applications, including global initiatives within the ISIMIP framework (Golub et al., 2022). The model is primarily designed for seasonally stratified, small-to-medium-sized lakes where vertical dynamics govern climate-driven oxygen depletion. Such systems are typically characterised by dimictic or monomictic mixing regimes, which represent the two most common lake types throughout the temperate zone (Wetzel, 2001). For lakes that are usually stratified but experience occasional mid-summer mixing, the framework can be adapted by incorporating a

constant oxygen replenishment term during these episodic events, as validated using observations from Lake Erken in 2019. Furthermore, the model is most applicable to lakes with stable trophic states. This is because the framework assumes that oxygen demand is driven by thermal–biogeochemical interactions rather than shifting nutrient loads.

Despite these advantages, the model relies on simplifying assumptions that define its optimal range of applicability. Because the model resolves changes only in the vertical dimension, it is less suitable for large, morphologically complex lakes where strong horizontal heterogeneity or internal seiches misrepresent the oxygen distribution (Bocaniov et al., 2020; Missaghi et al., 2013). Furthermore, the model is not intended for shallow polymictic lakes, where frequent mixing events prevent the development of stable hypolimnetic gradients. Moreover, our projections focus on the impacts of climate-change-driven shifts in lakes' thermal structure, excluding feedback mechanisms where climate change modifies oxygen consumption via changes in primary productivity and organic matter loading (Jenny et al., 2016; Weyhenmeyer et al., 2014; Woolway et al., 2020). Consequently, the model should be applied with caution in lakes undergoing substantial trophic change, such as eutrophication or oligotrophication. Additionally, in systems where methane oxidation (Bastviken et al., 2004) or inorganic chemical demand (Matzinger et al., 2010) dominate the oxygen budget, the assumption of stable depletion rates may fail. Finally, the reliance on simplified hydrodynamic forcing, including constant water levels and fixed parameter values across climate scenarios (Ayala et al., 2020), represents an inherent limitation that prioritises model transferability over site-specific complexity.

The wide ranges of acceptable model parameters (i.e., J_A and J_V) capture the inherent uncertainty in biogeochemical processes during summer stratification through both water-column and sediment oxygen consumptions. These parameters can be estimated using DO observation and can be combined into a single hypolimnetic oxygen depletion rate for the straightforward evaluation of climate-adaptive management. Empirical relationships between hypolimnetic oxygen depletion and external nutrient loading have been established in many lakes (Burns, 1995; Cornett and Rigler, 1987; Matzinger et al., 2010; Pace and Prairie, 2005; Rhodes et al., 2017; Rippey and McSorley, 2009; Walker, 1979). Moreover, numerous studies demonstrate that reducing nutrient inputs can successfully minimise deepwater deoxygenation (Carey and Migliaccio, 2009; Müller et al., 2014; Rhodes et al., 2017; Schindler, 2006; Søndergaard et al., 2005). Therefore, the oxygen depletion rate estimated by our model can be a proxy for preliminarily assessing the magnitude of nutrient reductions needed to achieve oxygen stability.

However, translating oxygen-based targets into detailed catchment or in-lake nutrient-reduction strategies must consider biogeochemical processes such as sediment carbon burial and internal nutrient recycling (Müller et al., 2012, 2019; Steinsberger et al., 2021). Therefore, coupled catchment–biogeochemical models are needed to develop nutrient management strategies (Crossman et al., 2019; Ladwig et al., 2021; Magee et al., 2019). As stratification duration is the strongest physical driver of future deoxygenation, mechanical interventions that disrupt stratification may offer additional mitigation and can be evaluated using advanced hydrodynamic and engineering models (Bryant et al., 2024; Li and Liu, 2018; Wüest et al., 1992).

Parameter ranges for J_A and J_V (at 20 °C) can be adapted from prior studies according to lake trophic status. For all trophic states, the minimum bound could be set at 0.01 g m⁻³ d⁻¹ for J_V and 0.01 g m⁻² d⁻¹ for J_A . However, maximum J_A values have been reported for oligotrophic (0.78 g m⁻² d⁻¹; Lardner-Cornett, 1982), mesotrophic (1.7 g m⁻² d⁻¹; Tasnim et al., 2021) and eutrophic lakes (3.2 g m⁻² d⁻¹; Mackenthun and Stefan, 1998). Maximum J_V values (oligotrophic: 0.16 g m⁻³ d⁻¹, mesotrophic: 0.85 g m⁻³ d⁻¹ and eutrophic: 1.78 g m⁻³ d⁻¹) can also be adopted from Table 1 in Nkwale et al. (2024). Improvements in long-term monitoring programmes and sensor technologies across diverse lake systems will further extend the applicability of this framework, improve the reliability of its outputs and reduce parameter

uncertainties. Moreover, to improve mechanistic insight, future work can explore how deepwater oxygen dynamics respond to extreme climatic forcing, such as heatwaves and heavy rainfall.

This modelling study advances understanding of the climate impacts on the in-lake physical mechanisms that govern deepwater oxygen dynamics. Oxygen is a fundamental component of lake ecosystems (Bernhardt et al., 2017; Carey, 2023), therefore maintaining stable oxygen is essential for safeguarding ecosystem functions. Prolonged anoxia accelerates internal nutrient release, stimulating primary production and further enhancing heterotrophic respiration, thereby reinforcing oxygen loss (Lewis et al., 2023). Concurrent surface warming and hypolimnetic deoxygenation limit habitable zones for fish (Jones et al., 2008; Kraus et al., 2023; North et al., 2014) and invertebrates (Galic et al., 2019), thereby threatening aquatic biodiversity. For instance, the common native fish species in Erken including Eurasian perch (*Perca fluviatilis*) and Northern Pike (*Esox lucius*) (Dill, 1993; Toner and Rougeot, 2008) are expected to face challenges for finding habitat with projected surface warming (Ayala et al., 2020) and deepwater oxygen declines. Anoxia also promotes the release of greenhouse gases (Hounshell et al., 2021; Zhu et al., 2023) and redox-sensitive metals (Beutel et al., 2008; Davison et al., 1982; Kang et al., 2019), degrading water quality and amplifying climate forcing. Therefore, maintaining deepwater oxygen under future climate change will be critical to preserving the ecological integrity of freshwater ecosystems.

5. Conclusion

We developed a simple deductive model that integrates key mechanisms driving vertical deepwater oxygen dynamics during summer stratification, including oxygen consumption from the sediment and the water column as well as oxygen transfer via diffusivity. The oxygen model performed reliably when applied in Lake Erken. This modelling framework identified prolonged stratification as the main driver of future climate-driven deoxygenation. It estimated the reduction in hypolimnetic oxygen depletion rate to mitigate this climate-driven deoxygenation. Results showed the levels of required intervention highly depend on the future trajectory of greenhouse gas emissions. Recent climate forcing tends to align more closely with high-emission scenario projections, emphasising the urgent need for stronger environmental policies and management actions. Nevertheless, even under the low-emission RCP2.6 scenario, some modest interventions will be necessary to maintain oxygen stability. This oxygen model is transferable to other seasonally stratified lakes where in-lake physical processes dominate vertical deepwater oxygen dynamics. To project the impact of future climate change, the model needs to be coupled with a calibrated hydrodynamic model. Implementing the management strategies targeting long-term oxygen stability would support sustainability in lake ecosystem services, including water supply, biodiversity, aquatic habitats and local economies. Ensuring the long-term effective mitigation of climate-driven deoxygenation will require coordinated efforts to address both emission reductions and local management practices.

CRedit authorship contribution statement

Mahtab Yaghouti: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ana I. Ayala:** Writing – review & editing, Validation, Resources, Methodology, Data curation, Conceptualization. **Jorrit P. Mesman:** Writing – review & editing, Validation, Software, Methodology, Data curation, Conceptualization. **Don C. Pierson:** Writing – review & editing, Validation, Resources, Methodology, Funding acquisition, Data curation, Conceptualization. **Tom Shatwell:** Writing – review & editing, Validation, Methodology, Conceptualization. **Lipa G.T. Nkwale:** Writing – review & editing, Validation. **Karsten Rinke:** Writing – review & editing, Validation, Methodology, Conceptualization. **Haoran Shi:** Writing

– review & editing, Validation, Methodology. **Eleanor Jennings:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **Peter Hunter:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **R. Iestyn Woolway:** Writing – review & editing, Validation, Supervision, Methodology. **Ian D. Jones:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

Code availability

The model scripts for simulating deepwater oxygen profiles in Lake Erken, developed using data from the Swedish Infrastructure for Ecosystem Science (SITES), are available in [this](#) GitHub repository. Climate scenario projections and related analyses are available upon request.

Declaration of competing interest

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

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement 956623. MSCA-ITN-ETN—European Training Network. inventWater (Inventive forecasting tools for adapting water quality management to a new climate). This study has been made possible by data provided by the Swedish Infrastructure for Ecosystem Science (SITES). We acknowledge the Global Lake Ecological Observatory Network (GLEON), in particular the EezyPeezyISIOxy project and thank all contributors involved in this initiative. We are grateful for the financial support to **A.I. Ayala** from the Swedish Research Council (VR) under project ID 2021-04639. **J.P. Mesman** and **D.C. Pierson** were funded by the European Union's Horizon 2020 research and innovation programme, grant agreement number 101017861 (SMARTLAGOON project) and by Formas - a Swedish Research Council for Sustainable Development - and the 2022 Joint Transnational Call of the European Partnership Water4All, grant agreement number 101060874 (MEWS project). Finally, we thank the editor and the two anonymous reviewers for their constructive and valuable feedback.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envsoft.2026.106941>.

Data availability

The model scripts for simulating deepwater oxygen profiles in Lake Erken, based on observed data, are available in shared GitHub repository link.

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