Environmental Science and Ecotechnology 28 (2025) 100631

Contents lists available at ScienceDirect

Environmental Science and Ecotechnology

journal homepage: www.journals.elsevier.com/environmental-science-and-ecotechnology/

Original Research

Tracking reservoir warming in a changing climate: A 31-year study from Czechia

Petr Znachor [a,b,*], Dušan Kosour [c], Luděk Rederer [d], Václav Koza [d], Vojtěch Kolář [a,b], Jiří Nedoma [a]

[a] Biology Centre of Czech Academy of Sciences, v.v.i., Institute of Hydrobiology, Na Sádkách 7, České Budějovice, 37005, Czechia
[b] Faculty of Science, University of South Bohemia, Branišovská 31, České Budějovice, 37005, Czechia
[c] River Morava Basin Board, State Enterprise, Dřevařská 11, 602 00, Brno, Czechia
[d] River Elbe Basin Board, State Enterprise, Víta Nejedlého 951/8, Slezské Předměstí, 500 03, Hradec Králové, Czechia

ARTICLE INFO

Article history:
Received 30 June 2025
Received in revised form
23 October 2025
Accepted 23 October 2025

Keywords:
Climate change
Time series
Long-term trends
Temperature
Variability

ABSTRACT

Freshwater reservoirs are critical for water management but face increasing impacts from climate change, which alters their thermal regimes and affects ecosystem functions globally. In temperate regions, surface water temperatures have risen at rates often surpassing those of air temperature, driven by atmospheric warming, hydrological processes, and reservoir morphometry. However, long-term studies on reservoir-specific thermal responses, particularly short-term variability, remain scarce. An important question is how environmental drivers influence both long-term warming trends and daily thermal fluctuations in managed water bodies. Here we show that over 31 years (1991–2021), surface water temperatures in 35 Czech reservoirs increased by an average of 0.59 °C per decade, with air temperature, altitude, and retention time as primary predictors of mean temperatures. A novel corrected metric for day-to-day variability (*DTDV*) revealed that inflow rate, depth, and retention time strongly influence short-term fluctuations, and *DTDV* trends positively correlated with warming rates, indicating linked drivers of thermal reorganization. Seasonal patterns showed strongest warming in April, with an anomaly of minimal change in May, likely tied to regional climatic shifts. These findings elucidate climate-driven thermal dynamics in reservoirs, highlighting the interaction of climatic and local factors. By combining statistical modeling with process-based indicators, this study informs adaptive strategies to mitigate impacts on water quality, stratification, and biodiversity under changing climates.

1. Introduction

Climate change is profoundly altering the physical, chemical, and biological dynamics of freshwater ecosystems worldwide. Lakes and reservoirs, which hold the majority of Earth's surface liquid freshwater, are particularly sensitive to climate-induced changes in temperature, ice cover, and hydrological balance [1,2]. Numerous studies have shown that surface water temperatures are increasing across a wide range of climate zones, often at rates exceeding those of the surrounding air, with global averages ranging from 0.24 to 0.34 °C per decade [3–5]. However, these trends show substantial regional, seasonal, and interannual variability, driven by local factors such as wind speed, water clarity, and morphometry [6,7] or even glacier meltwater and urbanization [8,9]. In some cases, lake surface warming outpaces atmospheric warming, especially during spring and early summer, when earlier stratification onset amplifies surface heating [10,11]. Conversely, increased evaporative cooling and thermal inertia may suppress warming in open or wind-exposed systems [5]. These thermal changes have widespread ecological repercussions, including altered stratification, oxygen depletion, enhanced evaporation, and shifts in thermal habitats that threaten native biodiversity [6,12,13]. Reductions in winter ice cover and earlier stratification onset are now key indicators of warming, particularly in temperate and polar lakes [2,14]. Furthermore, the emergence of

* Corresponding author. Biology Centre of Czech Academy of Sciences, v.v.i., Institute of Hydrobiology, Na Sádkách 7, České Budějovice, 37005, Czechia.
E-mail address: znachy@hbu.cas.cz (P. Znachor).

https://doi.org/10.1016/j.ese.2025.100631
2666-4984/

"no-analogue" thermal conditions, those outside historical variability, raises concerns about long-term ecosystem resilience [12]. As both climate sentinels and vital water resources, understanding how lakes and reservoirs respond to global warming remains a priority for climate science and water management.

While long-term temperature trends provide essential insight into climate change, short-term thermal fluctuations, especially day-to-day temperature variability (*DTDV*), are increasingly recognized as ecologically and socially impactful. *DTDV* reflects rapid weather changes that affect organismal physiology, ecosystem function, and human well-being [15,16]. Unlike seasonal or annual trends, *DTDV* captures high-frequency temperature shifts resulting from atmospheric dynamics, local topography, and surface energy balance [17,18]. Studies have shown that such variability often decreases with warming in many mid- and high-latitude regions, largely due to Arctic amplification and weakening meridional temperature gradients [19,20]. However, trends can be regionally diverse, with increases in *DTDV* observed in some areas due to local factors such as coastal proximity or urban heat effects [18,21]. It is important to note that all existing studies on *DTDV* have focused exclusively on air temperature, and to date, no comparable analyses have been conducted for surface water temperature. In freshwater lakes, *DTDV* is supposedly influenced by morphometric and geographic characteristics, such as depth and topographic shading, with deeper lakes typically exhibiting greater thermal stability [22]. Despite its potential significance for mixing processes, ice phenology, and biological dynamics, *DTDV* remains sparsely studied in inland waters, making its manifestation in freshwater reservoirs and its relationship to broader thermal trends a crucial yet underexplored dimension of climate change impacts.

Although numerous studies have investigated lake thermal responses to global climate change, Central European freshwater systems, especially artificial reservoirs, remain underrepresented in the literature. Most existing research in the region focuses on atmospheric parameters, such as air temperature, circulation types, and extremes [23,24], while comparable long-term analyses of lake or reservoir thermal regimes are rare [25]. Recent studies from the Czechia have documented significant warming of air temperatures and shifts in the frequency of extreme weather events, often linked to changing atmospheric circulation patterns [23,24]. However, the aquatic response to these changes, particularly in man-made reservoirs, remains poorly quantified [25]. A few localized studies in Central Europe suggest that reservoirs may exhibit distinct thermal trajectories from natural lakes due to their shallower depths, managed hydrology, and dynamic catchment conditions [26,27]. The complex interplay of climate forcing and catchment-level influences, such as land cover change or forest dieback, further complicates the interpretation of thermal trends in reservoirs. In Poland, for example, Wang et al. [28] reported high variability in lake warming rates and emphasized the importance of understanding regional hydrometeorological drivers. Despite these advances, large-scale, comparative studies focusing on long-term air–water thermal coupling across multiple reservoir systems in Central Europe over multi-decadal periods remain scarce. This gap is particularly evident for metrics beyond seasonal means, such as extremes and short-term variability, which are critical for ecological forecasting and water resource management.

In this study, we analyze long-term thermal dynamics in 35 Czech freshwater reservoirs using a consistent 31-year dataset (1991–2021) of daily air and water temperature records. Our primary aim is to characterize the magnitude, direction, and variability of surface water temperature trends and assess their relationship with concurrent air temperature changes. We pay particular attention to differences between air and water warming rates and seasonal asymmetries that may reflect changes in mixing regimes, stratification, or ice phenology. In addition to long-term trends, we quantify day-to-day temperature variability, an underexplored but ecologically relevant aspect of thermal behavior. By comparing *DTDV* patterns across reservoirs and relating them to morphometric, geographic, and climatic factors, we examine how physical attributes influence thermal stability. We also assess whether warming and short-term variability co-occur, potentially indicating shared drivers of thermal reorganization.

Specifically, we address three questions: (i) What are the long-term trends in surface water temperature, and how do they compare with air temperature trends? (ii) How does *DTDV* vary among reservoirs, and what are its key environmental drivers? (iii) Do warming and variability co-occur? We hypothesize that air temperature and altitude primarily control long-term warming, while hydrological and morphometric factors such as inflow, depth, and retention time shape short-term variability. Together, these analyses provide regionally grounded, statistically robust insights into how climate change is affecting managed freshwater systems in Central Europe.

2. Materials and methods

2.1. Freshwater reservoirs studied

Water temperature data were collected from 35 freshwater reservoirs in Czechia (Fig. 1) by the river-basin authorities, Povodí Labe (Elbe), Povodí Moravy (Morava), and Povodí Vltavy (Moldau), all state enterprises. The reservoirs span a wide range of characteristics: altitudes from 170 to 774 m above sea level, surface areas from 0.12 to 49 km^2, maximum depths from 3 to 58 m, volumes between 0.13 and 212 $\times$ 10^6 m^3, watershed areas from 4.3 to 11,850 km^2, and mean theoretical retention times of 0.96–432 days, calculated from long-term mean inflow rates and reservoir volumes provided by the respective basin authorities (see Supplementary Table S1).

2.2. Primary water temperature data and processing

Surface water temperature (T_w) was measured daily at 7 a.m. in the dam area over the period 1991–2021. The dataset was first cleaned to correct obvious errors, fill gaps, and ensure homogeneity. Specifically, isolated T_w values that deviated by more than

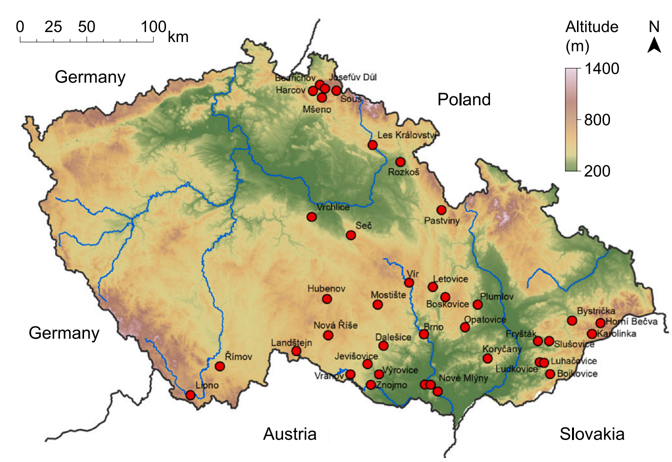

Fig. 1. Map of Czechia with the location of the freshwater reservoirs included in the study. For details, see the Supplementary Table S1.

3 °C from an otherwise stable temporal sequence were replaced either with the mean value or, in cases of suspected typographical or digitization errors, with the presumed correct value. Gaps in the time series were interpolated linearly, with resulting values rounded to one decimal place. Across all reservoirs, we filled 1223 gaps (mean length 3.5 days), affecting 4352 daily values (1.11% of records); 96.9% of gaps were ≤6 d, and 88% of filled days occurred in November–March (mean T_w 2.9 °C; details in Supplementary Table S2). In the November–March period, any T_w values below 1 °C were set to 0.5 °C. We identified extended winter runs of uniform entries (e.g., 0.0, 0.01, 0.1, or 1.0 °C) that varied by reservoir and likely reflected suspended sampling or placeholder logging under snow or ice. We treated these sequences as placeholders rather than measurements and applied this conservative homogenization to avoid data bias and artificial cross-reservoir differences. The proportion of original versus processed data for each reservoir is provided in Supplementary Table S2.

2.3. Air temperature data

Monthly averages of air temperature (T_{air}) were obtained from publicly available data from the nearest Czech Hydrometeorological Institute weather station. These stations were located on average 9.9 km from the respective reservoirs (range: 0–40 km) with altitude differences ranging from 3 to 401 m (mean: 42 m; see Supplementary Table S3). For each reservoir, air temperature trends were compared with water temperature trends.

2.4. Calculation of day-to-day variability in water temperature DTDV

To quantify short-term fluctuations in surface water temperature while controlling for underlying seasonal trends, we developed a corrected metric of *DTDV* that corrects for the confounding influence of seasonal trends. Traditional measures of *DTDV,* often based on the mean or standard deviation of daily changes, can be skewed by steady seasonal warming or cooling. Here, *DTDV* for each month was calculated as the mean of absolute daily temperature changes, minus the absolute value of the average net change:

$$DTDV = \frac{1}{N}\sum_{i=2}^{N+1}\left|T_{w,i} - T_{w,i-1}\right| - \left|\frac{1}{N}\sum_{i=2}^{N+1} T_{w,i} - T_{w,i-1}\right| \quad (1)$$

where $T_{w,i}$ is the water temperature on day i, and N is the number of days in the month. This formulation corrects for monotonic warming or cooling trends, which may artificially inflate *DTDV* in transitional months (e.g., April or November, see Supplementary Fig. S1 for explanation), while preserving meaningful variability due to weather events, hydrological inflows, or mixing dynamics.

2.5. Statistical evaluation

For each reservoir, we calculated the 31-year mean values of all variables and the linear trends (via ordinary linear regression [OLR]). Also, we computed Sen's slopes as nonparametric trend estimates; they were highly correlated with the OLR estimates ($R^2 = 0.893$–0.978). We tested whether the air and water temperature trends were parallel and assessed the correlations between these variables. Relationships between parameters describing surface water thermal behavior, used as response variables, were analyzed using linear correlations and generalized linear models (GLMs). The response variables included: long-term mean T_w, trends in T_w, mean *DTDV*, trends in *DTDV*, and the average difference between means in T_w and T_{air}. Explanatory variables (predictors) related to individual reservoir characteristics included surface altitude (*Alti*), maximum depth (Z_{max}), T_{air}, mean inflow rate (Q_i), and theoretical retention time (*TRT*). To reduce multicollinearity, predictor selection was performed by pairwise correlations and variance inflation factors, with values ranging from 2.00 to 3.52 [29]; see Supplementary Table S4 for the correlation matrix.

For each response variable, a candidate set of 24 GLMs (glm_1–glm_24) was constructed using all combinations of the five environmental predictors, ranging from full models to univariate and null models (Supplementary Table S5). All models assumed a Gaussian error distribution and identity link function. Model selection was based on the corrected Akaike Information Criterion (*AICc*), with models having $\Delta AICc < 2$ considered to have substantial support. For each model, we extracted *AICc* weight, R^2, normalized root mean square error (*nRMSE*), estimated regression coefficients, and predictor significance (p-values).

To enable comparison of prediction accuracy across response variables with differing scales, model residuals were evaluated using *nRMSE*, calculated as *RMSE* divided by the overall mean of the observed response variable and expressed as a percentage. This provides a scale-independent measure of model error, with lower values indicating better predictive accuracy. Only statistically significant predictors ($p < 0.05$) from top-ranked models were retained for interpretation. For the analysis of the average difference between T_w and T_{air} we used only the models not including T_{air} as a predictor to avoid autocorrelation, as it is inherently part of the response variable.

Statistical calculations were performed using GraphPad PRISM 10.2 for Windows (GraphPad Software, Boston, Massachusetts, USA, www.graphpad.com), Microsoft Excel 365 with Real Statistics Resource Pack software (Release 8.9.1). GLMs were conducted in R version v. 4.4.1 [30], using base functions. We checked model residuals using the package DHARMa (v. 0.4.6 [31]). If necessary, we transformed and summarized them using the packages bbmle for $\Delta AICc$, weight, and df (v. 1.0.25.1 [32]) and package performance for marginal R^2 (v. 0.12.3 [33]). We then used the function ggpredict in the package ggeffects (v. 1.7.1 [34]) for the most parsimonious model to extract the predicted data and visualised them in GraphPad PRISM 10.2.

3. Results

3.1. Air temperature

Long-term annual average of the T_{air} throughout the study at the nearest weather stations (Supplementary Table S2) ranged from 5.7 to 10.2 °C, with an overall mean of 8.3 °C (Fig. 2a, Supplementary Table S6). T_{air} was significantly negatively correlated with altitude ($R^2 = 0.651$, $p < 0.0001$), corresponding to a vertical temperature gradient of 0.56 °C per 100 m, a value slightly lower than the standard atmospheric lapse rate of 0.65 °C per 100 m [35]. The average seasonal pattern of T_{air} can be seen in Supplementary Fig. S2. Over the study period, T_{air} increased on average by 0.46 °C per decade (a total increase over 31 years of 1.41 °C; $R^2 = 0.282$, $p < 0.01$), trends in T_{air} increase at individual stations ranged from 0.24 to 0.71 °C per decade, with all but three trends reaching statistical significance (Fig. 2b–Supplementary Table S6). Monthly analysis revealed that warming was not uniform throughout the year: the most pronounced increases (0.80–1.03 °C per decade) occurred in June, November, and December, while May exhibited a non-significant decrease of 0.25 °C per decade and other months showed non-significant increases of 0.08–0.51 °C per decade. In months where the trend in

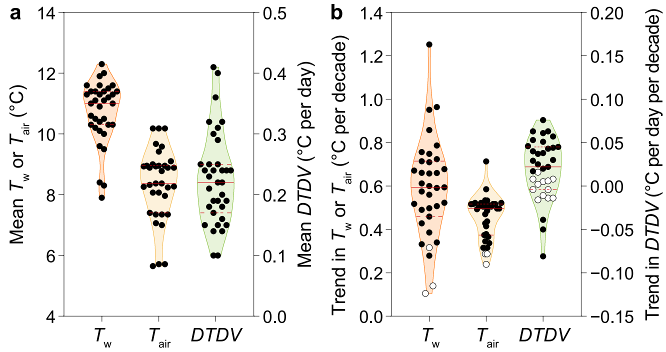

Fig. 2. Distribution of long-term means (**a**) and linear trends (**b**) in surface water temperature (T_w), air temperature (T_{air}), and day-to-day T_w variability (*DTDV*) across 35 Czech reservoirs during the period 1991–2021. Each point represents an individual reservoir; open symbols indicate statistically non-significant trends. Red lines denote the median, as well as the lower and upper quartiles.

increase in T_{air} was significant for the average of all reservoirs, it was also significant at 31–35 individual reservoirs, while in the remaining months, the trend was not significant at any reservoir (Supplementary Fig. S2).

3.2. Water temperature

Over the 31 years, the T_w annual mean ranged from 7.9 to 12.3 °C, with an overall mean of 10.7 °C (Fig. 2a–Supplementary Table S6). Mean T_w was significantly negatively correlated with surface altitude ($R^2 = 0.639$, $p < 0.0001$) and positively correlated with local mean T_{air} ($R^2 = 0.430$, $p < 0.0001$). GLMs for T_w mean performed strongly, with R^2 values between 0.81 and 0.83 and low

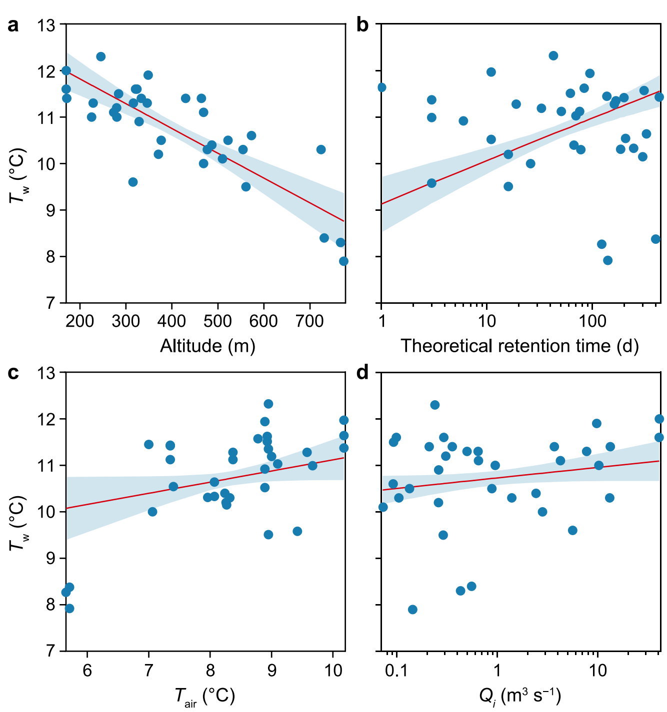

Fig. 3. Relationships between mean surface water temperature (T_w) and environmental predictors in the best-performing generalized linear model (GLM; glm_5) for 35 Czech reservoirs. Panels plot mean T_w plotted against surface altitude (**a**), theoretical retention time (**b**), mean air temperature (T_{air}; **c**), and mean inflow rate (Q_i; **d**). Red lines are the GLM fit with 95% confidence intervals (shading). Altitude, theoretical retention time, and T_{air} were significant predictors ($p < 0.05$), whereas Q_i was not. Model performance: $R^2 = 0.832$, *nRMSE* = 3.88%. See Table 1 for details.

nRMSE values (3.88–4.11%). Altitude, TRT, and T_{air} were the most influential and consistent predictors, with altitude showing a strong negative effect, while TRT and T_{air} had positive effects on T_w across models. This indicates that lower-elevation reservoirs with longer retention times and warmer air temperatures tend to have higher surface water temperatures (for details, see Fig. 3, Table 1).

All reservoirs exhibited a roughly linear increase in T_w over the study period, averaging an increase of 0.59 °C per decade (Fig. 4a; 1.83 °C over 31 years). Individual reservoir trends ranged from 0.10 to 1.25 °C per decade, with all but three reservoirs showing statistically significant trends (Fig. 2b–Supplementary Table S6). Linear regression analysis indicated that the rate of warming did not significantly correlate with the reservoir characteristics examined, nor could differences be explained by local T_{air} trends. T_w trend GLMs had low explanatory power ($R^2 \leq 0.18$) and high *nRMSE* values (34.9–38.5%), indicating weak ability to explain inter-reservoir variability in long-term warming rates. Most models had no significant predictors, though altitude appeared in two models with weak but statistically significant effects. ($R^2 = 0.12$–0.17; Table 1). Monthly trends in T_w varied: the most rapid warming occurred in April, followed by August and October (0.82–1.02 °C per decade, with a maximum increase of 3.2 °C over 31 years), whereas February and May showed the slowest warming (approximately 0.25 °C per decade). Except for May, these average monthly trends were statistically significant. At the individual reservoir level, significant monthly trends in T_w were observed in 18–31 reservoirs for all months except September and May (only 13 and 2 reservoirs, respectively; Fig. 5).

3.3. Relationship between T_w and T_{air}

Interannual variability in T_w was primarily driven by fluctuations in T_{air} (Fig. 4a and b). Annual averages of T_w across all reservoirs were highly correlated with corresponding T_{air} averages ($R^2 = 0.863$, $p < 0.0001$; Fig. 6a and b), indicating a tight (zero-lag) cross-correlation. For detrended data, the correlation increased further ($R^2 = 0.912$, $p < 0.0001$; Fig. 6c and d). Interestingly, both average and maximum deviations from the trends were greater for T_{air} than for T_w (0.52 °C and 1.58 °C versus 0.35 °C and 0.94 °C, respectively; Fig. 6c), the difference in averages being highly statistically significant ($p < 0.0001$, paired *t*-test). At the individual reservoir level, cross-correlation coefficients between T_w and T_{air} ranged from 0.445 to 0.931 (Supplementary Table S6). Although the average slopes of T_{air} (0.46 °C per decade) and T_w (0.59 °C per decade) differed, this difference was not statistically significant ($p = 0.421$), suggesting parallel trends. Also at the individual reservoir level, 28 out of 35 exhibited parallel trends (Supplementary Table S6). In six reservoirs, T_w increased significantly faster than T_{air}, while in only one reservoir was the opposite observed. The average difference between T_{air} and T_w varied substantially (0.2–4.4 °C) with an overall mean of 2.4 °C. The differences were positively correlated with maximum depth (Z_{max}; $R^2 = 0.292$, $p < 0.001$) and TRT ($R^2 = 0.370$, $p < 0.001$). GLMs for T_w–T_{air} mean difference performed moderately well ($R^2 = 0.50$–0.54), with *nRMSE* between 25.8% and 26.9%. TRT and altitude were both significant, with TRT showing a strong positive effect and altitude a weak negative effect (Table 1, Supplementary Fig. S3).

3.4. Day-to-day variability in water temperature

The mean *DTDV* over the entire period was 0.23 °C per day, with individual reservoirs ranging from 0.10 to 0.41 °C per day (Fig. 2a–Supplementary Table S7). It was positively correlated with Q_i ($R^2 = 0.179$, $p < 0.05$) and negatively correlated with Z_{max}

Table 1
Summary of statistically significant predictors ($p < 0.05$) in the best-performing generalized linear models (GLMs, $\Delta AICc < 2$) for five surface water temperature parameters across 35 Czech reservoirs over 31 years (1991–2021).

Parameter	GLM model	k	ΔAICc	W	R^2	nRMSE (%)	Significant predictors	Estimate	p
T_w mean	glm_5	4	0.0	0.330	0.832	3.88	*Alti*	−0.0053	<0.001
							TRT	0.91	<0.001
							T_{air}	0.24	0.045
	glm_4	4	0.8	0.224	0.828	3.93	*Alti*	−0.0052	<0.001
							TRT	0.64	<0.001
							T_{air}	0.29	0.016
	glm_9	3	1.2	0.184	0.811	4.11	*Alti*	−0.0052	<0.001
							TRT	0.78	<0.001
							T_{air}	0.27	0.032
T_w trend	glm_24	0	0.0	0.145	0.000	38.5	None	-	-
	glm_21	1	0.5	0.113	0.053	37.5	None	-	-
	glm_19	1	0.6	0.109	0.051	37.5	None	-	-
	glm_15	2	0.6	0.108	0.118	36.3	*Alti*	0.0008	0.040
	glm_10	3	0.9	0.093	0.177	34.9	*Alti*	0.0008	0.035
DTDV mean	glm_18	2	0.0	0.194	0.552	22.2	Z_{max}	−0.15	<0.001
							Q_i	0.039	0.001
	glm_3	4	0.9	0.125	0.609	20.4	Z_{max}	−0.12	0.006
	glm_7	3	0.9	0.122	0.574	20.4	Z_{max}	−0.11	0.013
	glm_13	2	1.0	0.119	0.539	22.2	*TRT*	−0.056	0.001
	glm_8	3	1.5	0.094	0.568	21.7	*TRT*	−0.067	<0.001
							Z_{max}	−0.082	0.037
	glm_11	3	1.8	0.078	0.563	21.7	Z_{max}	−0. 17	<0.001
							Q_i	0.044	0.001
	glm_2	4	2.0	0.073	0.597	20.9	Z_{max}	−0.12	0.006
DTDV trend	glm_7	3	0.0	0.154	0.238	158	Q_i	−0.027	0.004
							Z_{max}	0.058	0.029
							TRT	−0.029	0.041
	glm_21	1	0.1	0.147	0.111	168	Q_i	−0.014	0.042
	glm_2	4	0.6	0.115	0.287	153	Q_i	−0.030	0.001
							Z_{max}	0.067	0.013
	glm_11	3	0.7	0.110	0.223	158	Q_i	−0.021	0.008
	glm_16	2	1.5	0.072	0.140	168	Q_i	−0.018	0.023
	glm_18	2	1.7	0.066	0.136	168	Q_i	−0.014	0.049
	glm_24	0	1.8	0.062	0.000	179	None	-	-
T_w–T_{air} mean difference	glm_8	3	0.0	0.333	0.541	25.8	*TRT*	0.92	<0.001
							Alti	−0.0020	0.013
	glm_14	2	0.2	0.296	0.500	26.9	*TRT*	1.13	<0.001
							Alti	−0.0019	0.024

Note: The modeled parameters include long-term mean surface water temperature (T_w mean), long-term trend in T_w (T_w trend), mean day-to-day variability in T_w (*DTDV* mean), long-term trend in *DTDV* (*DTDV* trend), and mean difference between T_w and air temperature (T_w–T_{air} mean difference). Predictors include mean air temperature (T_{air}), surface altitude (*Alti*), maximum depth (Z_{max}), mean inflow rate (Q_i), and mean theoretical retention time (*TRT*). For the analysis of the T_w–T_{air} mean difference, T_{air} was excluded as a predictor to avoid mathematical autocorrelation. Table columns include the model identification, number of predictors (k), $\Delta AICc$ (difference from the top-ranked model), Akaike weight (W), coefficient of determination (R^2), and normalized root mean square error (*nRMSE*, expressed as a percentage of the overall mean of the modeled parameter). *nRMSE* provides a scale-independent indicator of model prediction accuracy, with lower values indicating a better fit. Only statistically significant predictors ($p < 0.05$) are shown. For a complete list of candidate models and predictors included, see Supplementary Table S5.

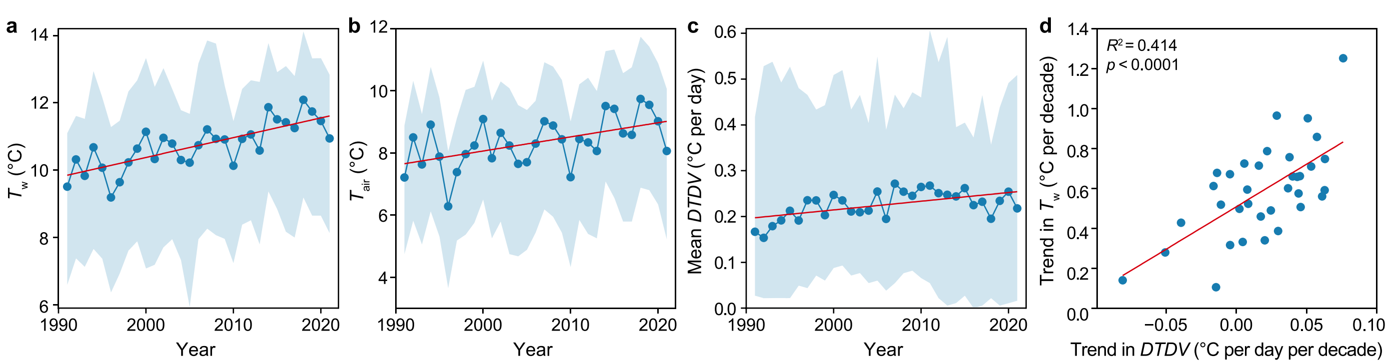

Fig. 4. **a**–**c**, Long-term trends in surface water temperature (T_w; **a**), air temperature (T_{air}; **b**), and day-to-day T_w variability (*DTDV*; **c**) in 35 Czech reservoirs. Points are annual means across reservoirs; the blue band shows the minimum–maximum range; red lines show linear trends. **d**, Relationship between steepness of trends in T_w and *DTDV* in individual reservoirs, represented by blue points. The red line shows the linear trend.

($R^2 = 0.380$, $p < 0.0001$) and TRT ($R^2 = 0.369$, $p < 0.001$). The average seasonal pattern in *DTDV* is evident from Supplementary Fig. S4. GLMs of mean day-to-day variability in T_w showed moderate explanatory power ($R^2 = 0.54$–0.61) and *nRMSE* values between 20.4% and 22.2%. Z_{max} was the most consistent predictor, always negatively associated with *DTDV*. TRT and Q_i also contributed to several models (Table 1, Supplementary Fig. S5).

The overall long-term trend in *DTDV* was significantly

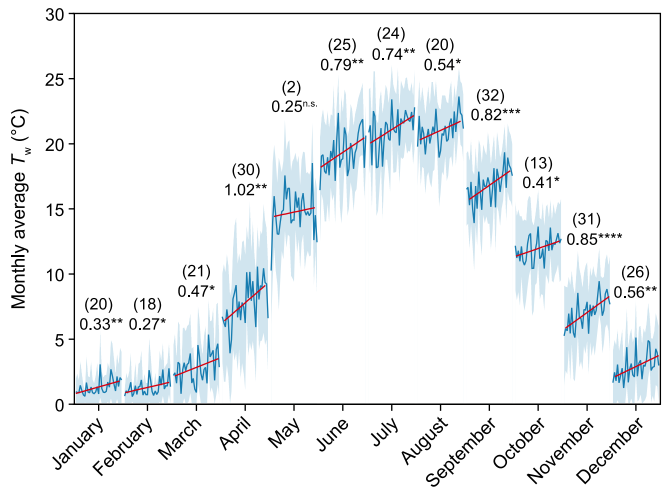

Fig. 5. Monthly changes in mean average water temperatures (T_w) across 35 Czech reservoirs between 1991 and 2021. Blue lines show reservoir-level monthly means; the blue band spans the minimum–maximum range across the reservoir; red lines indicate linear trends. Numbers in parentheses indicate the number of reservoirs with a significant positive trend in T_w. Numbers on the second line are trend slopes (°C per decade); asterisks denote statistical significance (*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; ****$p < 0.0001$), n.s.: not significant.

increasing at 0.019 °C per day per decade ($p < 0.001$, $R^2 = 0.316$), though individual reservoir trends varied vastly from −0.081 to 0.076 °C per day per decade. Trends were significantly increasing in 20 reservoirs, non-significant in 12, and significantly decreasing in three (Fig. 2b–Supplementary Table S7). Moreover, many *DTDV* trends exhibited non-linear patterns such as deceleration or shifts in behavior in the latter half of the study period (Fig. 4c). Therefore, Sen's slopes were reported alongside linear regression slopes, with both estimates being highly correlated ($R^2 = 0.978$). At the reservoir level, trends in *DTDV* were only weakly negatively correlated with Q_i ($R^2 = 0.115$, $p < 0.05$) and reservoir volume ($R^2 = 0.114$, $p < 0.05$). GLMs for trends in *DTDV* performed weakly, with low R^2 values (0–0.29) and very high *nRMSE* (153–179%), suggesting poor model accuracy. Inflow rate appeared as a significant negative predictor in most models, while Z_{max} and TRT showed weaker or inconsistent effects (Table 1, Supplementary Fig. S6). Notably, a strong and highly statistically significant positive relationship was observed between trends in *DTDV* and corresponding trends in T_w ($R^2 = 0.414$, $p < 0.0001$; Fig. 4d). As for trends in monthly average *DTDV*, significant increasing trends were detected only in April and December (0.057 and 0.020 °C per day per decade, respectively). In contrast, non-significant increases (ranging from 0.011 to 0.037 °C per day per decade) were observed in other months, except for October and November, which exhibited marginally decreasing trends (−0.001 and −0.007 °C per day per decade, respectively). At the individual reservoir level, significant increasing monthly trends in *DTDV* were identified in 1–21 reservoirs, while significant decreasing trends were observed in up to 3 reservoirs (Supplementary Fig. S4).

4. Discussion

4.1. Long-term temperature trends

The pronounced surface water warming observed in Czech reservoirs (~0.59 °C per decade, range: 0.10–1.25 °C per decade) is consistent with, but slightly exceeds, the rates typically reported for lakes in the temperate climate zone. Numerous recent studies across Europe and North America have confirmed widespread and significant increases in lake surface water temperature over the past several decades, with notable implications for aquatic ecosystems. O'Reilly et al. [3], in a landmark synthesis of 235 globally distributed lakes, reported an average summer surface warming rate of 0.34 °C per decade from 1985 to 2009, with a clear signal of enhanced warming in temperate-zone lakes. European studies have further shown substantial regional variability: for example, in Central European lakes, Woolway et al. [11] documented annual increases in T_w ranging from 0.2 to 0.5 °C per decade over the last half-century, with the strongest warming generally occurring in spring and early summer. Similarly, Dokulil [7] found that annual maximum surface water temperatures in ten European lakes increased at an average rate of 0.58 °C per decade between 1966 and 2015, with inter-lake differences related to local climate, lake morphometry, and geographic location. Long-term data from Hungarian lakes and rivers further confirm these patterns, revealing intensified surface water warming over the past 150 years [36]. Recent findings from Poland's lowland lakes [28] corroborate these trends, with annual warming rates ranging from 0.14 to 0.69 °C per decade, and even higher values recorded in some summer months. These values demonstrate a broad alignment with the trends observed in Czech reservoirs.

Importantly, studies from northern Europe suggest that surface warming rates in high-latitude lakes can vary substantially depending on local climatic drivers. In Lake Inari, a pristine Arctic

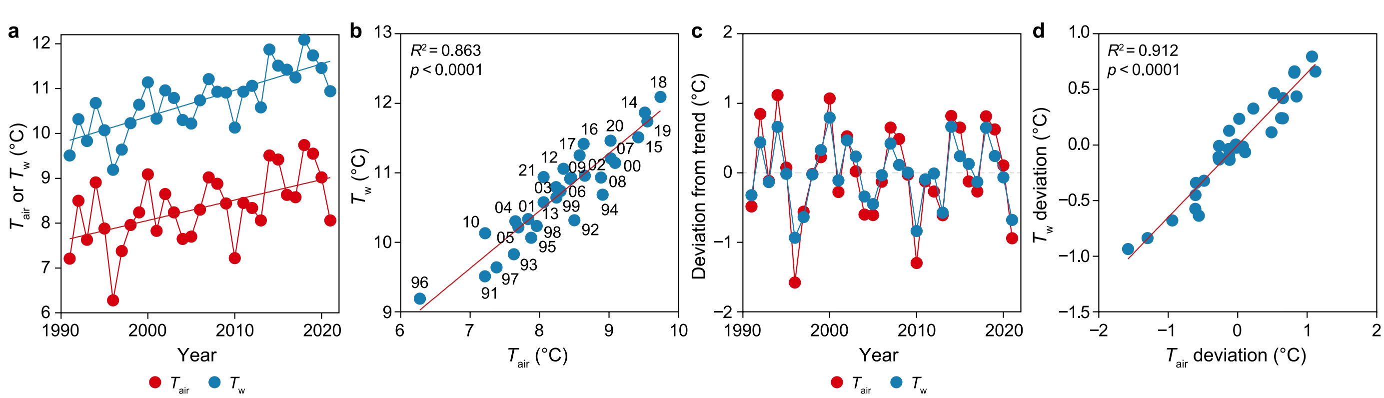

Fig. 6. Comparison of trends in surface water temperature (T_w) and air temperature (T_{air}). **a**, Trends in annual mean temperatures from 1991 to 2021; symbols represent averages across 35 Czech reservoirs, and lines indicate linear trends. The trends in T_w and T_{air} are not significantly different ($p = 0.421$). **b**, Correlation between corresponding annual means of T_w and T_{air}; each symbol represents one year (averaged across all reservoirs), with years labelled. **c**, Annual deviations of T_w and T_{air} from their respective long-term linear trends. **d**, The correlation between these detrended anomalies, emphasizing their interannual covariation independent of overall warming.

Lake in northern Finland, a six-decade dataset revealed a significant surface water warming trend of 0.25 °C per decade during summer (July–September), while deep water temperatures remained largely unchanged, indicating intensified summer stratification [37]. In contrast, Lake Kallavesi in central Finland experienced strong and statistically significant warming trends not only at the surface, but also in deep and depth-averaged water temperatures, with surface and bottom waters warming at rates close to or even exceeding local air temperature trends [38]. These northern lakes thus illustrate region-specific warming patterns: while both are experiencing the impacts of climate change, the thermal response varies due to local factors such as lake morphometry, ice cover duration, and atmospheric teleconnections.

Long-term reconstructions indicate that surface water warming accelerated markedly after the 1980s, reflecting both gradual climate change and punctuated climate regime shifts [4,11]. Overall, the rates reported for Czech reservoirs are at the upper end but within the range observed in similar climatic settings, aligning especially closely with recent European multi-lake syntheses [7,11,28]. This supports the growing consensus that temperate zone lakes and reservoirs are experiencing significant, and in some cases, accelerating warming, with profound ecological consequences.

The ecological consequences of surface water warming are wide-ranging and increasingly evident across temperate freshwater systems. One major outcome is the intensification and prolongation of thermal stratification, which reduces vertical mixing [39]. Warming-induced declines in oxygen solubility have contributed to widespread lake deoxygenation, while longer and stronger stratification further enhances bottom-water hypoxia, especially in eutrophic and mesotrophic reservoirs, by limiting vertical mixing and promoting oxygen depletion through microbial decomposition [40]. Anoxic conditions can further trigger internal loading of phosphorus, reinforcing eutrophication and promoting bloom-forming taxa. Elevated surface temperatures also shift plankton phenology, advancing the timing of key successional events such as spring diatom blooms, potentially decoupling food web interactions [39]. Perhaps most critically, warming has been strongly linked to the increasing frequency, duration, and intensity of cyanobacterial blooms [41]. Cyanobacteria are favored in warmer, stratified conditions due to their high temperature optima and physiological traits such as buoyancy regulation [42]. These blooms pose risks not only to biodiversity and ecosystem functioning but also to water quality, public health, and reservoir management. Collectively, these processes highlight that surface water warming is not a passive climatic signal, but an active driver of ecological change in freshwater reservoirs.

4.2. Factors affecting reservoir thermal patterns

Warming rates in lakes and reservoirs are highly variable and reflect a complex interplay between regional climate forcing and site-specific characteristics such as depth, surface area, catchment land use, and management practices [43,44]. In our analysis, thermal dynamics of Czech reservoirs were shaped by a combination of climatic and hydromorphological drivers, with their relative importance differing across thermal metrics. The most influential predictors included surface altitude, TRT, Z_{max}, and Q_i. These variables affected long-term mean surface temperatures, day-to-day variability, and the degree of thermal coupling with air temperature.

Consistent with previous studies [45,46], T_w was positively associated with TRT and T_{air}, and negatively with altitude. Reservoirs situated at lower elevations, with longer residence times and higher ambient T_{air}, tended to exhibit higher T_w. The influence of TRT likely reflects thermal inertia: in systems with low flushing rates, prolonged residence time allows greater absorption and retention of solar heat [47,48]. This can elevate surface temperatures and enhance the persistence of summer stratification. In contrast, long-term trends in T_w were only weakly explained by the tested predictors. Although altitude appeared in a few top-performing models, their low explanatory power (typically $R^2 < 0.2$) suggests that spatial variability in warming rates is shaped by more complex, site-specific processes, not captured by our variable set. Potential drivers include land-use changes in reservoir catchments (e.g., increased urbanization, deforestation, or agricultural intensification) that can influence thermal inputs via altered runoff characteristics, turbidity, or nutrient loading [49], local wind patterns influencing stratification and heat exchange [39,50], or reservoir operation regimes, such as drawdowns and artificial mixing. Internal processes (e.g., groundwater inflows, sediment heat fluxes), though unexamined here, may also contribute. This aligns with findings that lakes often display individual thermal trajectories even under similar climatic conditions [3,50], and understanding these trajectories will require integrated approaches that combine climatic, hydromorphological, land-use, and management data.

The difference between T_w and T_{air}, used here as a proxy for air–water thermal decoupling, was best explained by TRT and altitude. In reservoirs with long residence times, delayed responses to short-term atmospheric fluctuations can result in T_w exceeding T_{air} during warm periods. Conversely, higher-altitude systems may experience stronger coupling due to increased wind exposure and reduced heat accumulation. These findings are consistent with studies that emphasize the role of morphometry and hydrology in modulating atmospheric–aquatic thermal coupling [1].

The reservoir morphometric features also shape both the magnitude and seasonality of warming. Shallow or small-volume lakes tend to mix more frequently and can warm or cool rapidly, while deeper, stratified systems may experience more persistent surface warming, with deeper layers lagging [51]. Some studies suggest that shallow lakes are more sensitive to T_{air} changes [40], whereas others have shown greater surface warming in deeper, clearer lakes due to reduced vertical mixing [51]. Water clarity and trophic status also influence heat absorption [4,11]: transparent systems may warm more rapidly, while eutrophic waters may respond differently due to light attenuation by phytoplankton; however, these data were not available for the whole reservoir dataset. Nonetheless, the prevailing warming signal across reservoirs appears largely driven by atmospheric conditions. Even downstream of large dams, such as China's Three Gorges, surface waters have warmed at rates (~0.58 °C per decade) similar to natural lake systems [52]. While some lakes have warmed more rapidly than air due to earlier stratification, reduced wind speeds, or increased transparency [7,10], recent global analyses indicate that, on average, T_w may now be increasing slightly more slowly than T_{air}, largely due to increased evaporation, though Central Europe remains a regional exception to this trend [5].

Anthropogenic operations such as water level drawdowns, altered inflow regimes, or artificial mixing can further complicate thermal responses. While the prevailing warming signal across reservoirs appears largely driven by atmospheric conditions, management interventions can, in some cases, override climatic forcing. A striking example comes from the Brno Reservoir. In terms of morphometry and hydrodynamics (Z_{max} 19 m, surface area 2.59 km^2, volume 13×10^6 m^3, TRT 19.4 days), Brno would be expected to warm at ~0.5–0.6 °C per decade, close to the dataset average. Yet it exhibited the lowest and statistically insignificant warming of all study sites (0.1 °C per decade). This anomaly can be explained by a suite of remediation measures implemented to combat recurrent cyanobacterial blooms, including inflow phosphorus precipitation, bottom drying, liming, and fish stock manipulation [53]. Most importantly, since 2010, 15 mixing towers have continuously pumped hypolimnetic water upward, effectively suppressing surface warming. This case highlights how remediation strategies designed to improve water quality may unintentionally alter long-term temperature trajectories. Such management-driven thermal modifications need to be considered when interpreting reservoir temperature records and assessing climate impacts.

4.3. Seasonal heterogeneity in surface water warming

Long-term trends in lake and reservoir surface temperatures across the temperate zone frequently exhibit marked seasonal heterogeneity, with different months warming at different rates [10,11]. While many studies report the most rapid warming during spring, often attributed to earlier onset of stratification and an extended heating season [4], this is not a universal pattern. In our analysis of Czech reservoirs, we found that April exhibited the strongest surface warming (averaging 0.8–1.0 °C per decade), whereas May showed the weakest warming (~0.25 °C per decade), and trends were statistically non-significant at most sites. Similar findings have emerged from other regions. For example, in a study of 25 Polish lakes, Wang et al. [28] reported that spring warming was weaker than warming in summer or autumn. In six long-term monitored lakes in Wisconsin, USA, Lathrop et al. [43] observed peak warming in September. In contrast, a recent study from Hungary reported the fastest warming in winter and spring, followed by autumn and summer [36]. Globally, the seasonal timing of maximum warming varies by region: Central European lakes tend to warm most rapidly in spring, while warming in British and Irish lakes peaks in winter, and in Lake Superior during summer [1]. These patterns demonstrate that seasonal warming is shaped by both regional climate and lake-specific characteristics, and caution against using summer-only data to infer broader thermal trends [10].

4.4. Temporal asymmetry within spring

An especially striking pattern in our dataset is the contrast between strong warming in April and the absence of a significant trend in May (Fig. 5). Air temperature trends show a similar pattern, with an even negative trend in May (Supplementary Fig. S2), reinforcing the view that surface water thermal behavior is closely coupled to atmospheric conditions. This consistent asymmetry across most reservoirs and in air temperature records points to a common climatic driver. While individual cold years near the end of the study period may contribute to dampening the May trend [23], our analysis of air temperature trends at nearby stations adjacent to the studied reservoirs matched national averages closely ($R^2 = 0.995$), and the negligible May trend has persisted over four decades (1985–2024, not shown). This reinforces the conclusion that spring warming in Central European lakes and reservoirs is not uniformly distributed across months, and that apparent trend anomalies in May are robust features of the thermal regime.

The muted warming observed in May likely reflects broader atmospheric dynamics. Although detailed attribution is beyond the scope of this study, the persistence of the weak May trend over multiple decades suggests a climatic origin, potentially linked to late-spring circulation anomalies, atmospheric blocking events, or land–atmosphere feedbacks [54,55]. For instance, Ionita et al. [56] showed that the period 2007–2020 was characterized by a reduction of ~50% of the usual April rainfall amount in combination with extremely high air temperatures over large areas in central Europe, while no such anomalies have been noticed in May.

Recent research by Kopáček et al. [27] provides one of the possible mechanistic explanations for this “May anomaly.” Their long-term analysis of Bohemian Forest lakes (1998–2022) revealed a significant and persistent increase in May cloudiness, which led to reduced incoming solar radiation and stagnant or even declining air temperature during this month. This regional increase in May cloud cover appears to offset the expected warming signal from global climate change. In contrast, cloudiness in March and April has decreased over the same period, helping to explain the more pronounced warming earlier in spring. This pattern is consistent with broader findings across Europe, where increases in cloudiness have been linked to local cooling or reduced warming [57], while decreases in cloud cover result in enhanced solar heating.

Hydrological conditions, such as higher inflows and unstable stratification, may further contribute to thermal inertia in surface waters during this month. While increased concentrations of colored dissolved organic matter from catchments (brownification) can amplify warming under stable conditions [58,59], its effect may be diminished in May due to stronger mixing. Overall, the divergence between April and May warming underscores the importance of examining climate responses at a monthly resolution and highlights a seasonal “stall” in surface warming during late spring. The inclusion of cloud cover and atmospheric circulation dynamics into future climate and lake thermal models may improve the mechanistic understanding of such seasonal asymmetries.

4.5. Day-to-day temperature variability approach

To avoid conflating gradual seasonal warming with short-term fluctuations, we introduced a corrected *DTDV* metric. Traditional *DTDV*, defined as the absolute difference in temperature between two consecutive days, tends to increase during spring and summer simply because of the underlying seasonal warming trend. Our correction subtracts the net monthly change before averaging daily differences, enabling a more accurate measure of high-frequency thermal variability driven by short-term processes such as weather events, inflow pulses, or mixing disturbances. This correction ensures that *DTDV* reflects genuine high-frequency instability rather than long-term seasonal warming. While *DTDV* is a well-established concept in atmospheric sciences, frequently applied to assess thermal variability and its ecological consequences [17,18,20], its application to aquatic systems remains limited. Few studies have accounted for background seasonal drift when quantifying water temperature variability [16,60]. Our corrected *DTDV* thus represents a conceptual advance by allowing clearer comparisons across time and space, free from the artifact of seasonal slope. From an ecological standpoint, capturing short-term variability is particularly important, as aquatic organisms respond more directly to rapid fluctuations than to long-term trends. Short-term thermal instability can affect metabolic rates, stress responses, growth, reproduction, and species interactions [22,60,61]. It also influences ecosystem-level processes such as mixing, stratification, nutrient cycling, and bloom development.

Our analysis showed that hydromorphological features of reservoirs modulate *DTDV* patterns. Deeper reservoirs with longer TRT tend to have lower *DTDV* values, likely due to the dampening effect of higher thermal inertia and stable stratification regimes. Conversely, reservoirs with high inflow rates showed elevated *DTDV*, likely resulting from inflow-driven mixing that enhances surface temperature fluctuations. This is consistent with findings by Novikmec et al. [22] and Doubek et al. [60], who linked such patterns to both lake depth and storm-induced turbulence.

With climate change expected to increase the frequency and intensity of storms [60,62], corrected *DTDV* may serve as a useful indicator of short-term physical instability in lakes and reservoirs. Storms often trigger rapid thermal changes through wind-driven mixing and precipitation, which can temporarily disrupt stratification. While surface temperature shifts are often modest (<2 °C), their ecological consequences, such as changes in light availability and nutrient redistribution, can be significant [62]. Elevated *DTDV* values may thus indicate disturbances that reset or disrupt successional dynamics in phytoplankton assemblages. Such disturbances may prevent dominance by competitive taxa like bloom-forming cyanobacteria and instead favor opportunistic or fast-growing taxa, such as diatoms [62,63]. For instance, Thran-Khac et al. [64] observed that storm-driven mixing events coincided with temporary shifts away from cyanobacterial dominance in a eutrophic reservoir, while Znachor et al. [63] documented increased growth and enhanced vertical redistribution of diatoms after extreme rainfall. Corrected *DTDV* may thus reflect ecologically meaningful disturbances that reshape community structure, especially in reservoirs where vertical monitoring is limited. As a cost-effective surface-based metric, it offers potential for early warning of instability or increased bloom risk under future climate variability.

Interestingly, we found a strong positive correlation between long-term trends in T_w and *DTDV*, despite both being only weakly explained by the tested predictors. This suggests shared external drivers such as wind patterns or solar radiation, or internal feedbacks like changing stratification regimes [1,65]. By filtering out seasonal trends, our corrected *DTDV* helps isolate these dynamics and may serve as a valuable complementary tool for climate impact assessments. In many freshwater systems, ecological responses may be more tightly coupled to variability than to mean warming trends. Finally, by adapting the *DTDV* framework from atmospheric sciences to surface water temperature, we provide a new perspective for aquatic systems. The relationships we observed between *DTDV*, morphometry, and inflow suggest that similar processes shaping air temperature variability also operate in lakes and reservoirs, but are additionally modulated by water column structure, retention time, and human interventions.

4.6. Linking DTDV with water column stability: the case of the Římov Reservoir

Among all studied reservoirs, the Římov Reservoir (Z_{max} 43 m, surface area 2.1 km^2, volume 34×10^6 m^3, TRT ~100 days) stands out as the only site with long-term, detailed data on both *DTDV* and vertical stability of the water column [26]. This unique dataset enables us to explore the mechanistic underpinnings of *DTDV* in greater depth. Specifically, we observed an inverse relationship between *DTDV* and water column stability ($R^2 = 0.425$, $p < 0.001$, Supplementary Fig. S7) over the period 1998–2021, which reinforces the interpretation of corrected *DTDV* as a meaningful indicator of thermal instability. Elevated *DTDV* in periods of low stability supports the notion that short-term surface temperature fluctuations are amplified under weaker stratification and more frequent mixing, conditions common in hydrologically dynamic or meteorologically sensitive periods. The Římov Reservoir is one of the most intensively studied reservoirs in Europe and has served as a model system for decades [26,66,67]. In our study, the reservoir exhibited a significant but moderate long-term warming trend in T_w (0.47 °C per decade), closely aligning with both the Czech reservoir average and comparable European temperate lakes. Its seasonal warming pattern was typical, with the strongest trends in spring and early summer. Importantly, the reservoir did not exhibit thermal anomalies or abrupt variability trends over the 31 years, suggesting relative resilience to external disturbances. Prior studies also point to its stable hydrological regime and trophic state as key factors contributing to its predictable thermal behavior [26,67]. The coupling of *DTDV* with stratification metrics in the Římov Reservoir highlights the potential for using short-term variability as a proxy for deeper structural changes in reservoir thermal regimes. In systems where full vertical monitoring is not feasible, corrected *DTDV* could offer a cost-effective indicator of dynamic shifts in water column stability, particularly relevant under scenarios of increasing climate variability.

5. Study limitations and future directions

While our analysis is based on one of the most comprehensive long-term datasets of reservoir surface temperatures in Central Europe, several limitations should be acknowledged. First, although data gaps in the temperature records were infrequent and generally short, interpolation may introduce a small degree of uncertainty, even if unlikely to affect the long-term trends reported. Second, air temperature was derived from gridded datasets at a regional scale, which may not fully capture fine-scale variability in local meteorological conditions. Third, although our dataset covers 35 reservoirs, representing a relatively high number compared to most regional studies, it does not encompass the full diversity of reservoirs even within Czechia, especially at the extremes of morphometry, size, and operational regimes. Fourth, while longer-term datasets exist for several of the reservoirs, we limited our analysis to the 1991–2021 period to ensure consistency and comparability across all study sites. Finally, some potentially important drivers of thermal variability, such as water transparency, trophic state, and detailed operational data, were unavailable for the full dataset and could not be included in the statistical models. Recognizing these limitations is important for contextualizing our findings, while also highlighting avenues for future research.

6. Conclusions

Present results highlight the critical role of water column stability and stratification processes in shaping surface temperature dynamics in reservoir systems. Deep, low-elevation reservoirs with long retention times are predisposed to stronger and more persistent thermal stratification, reduced diel temperature fluctuations, and a greater decoupling from atmospheric temperatures. These features have profound ecological consequences, affecting oxygen and nutrient distribution, biogeochemical cycling, and the thermal habitat availability for aquatic organisms [40,68]. Conversely, reservoirs with high inflow rates and shallow morphometry are more susceptible to hydrologically driven mixing and thermal instability. Given projected increases in air temperature and changes in hydrological regimes due to climate change [69], these findings have significant implications for the future thermal behavior of artificial water bodies. Models that incorporate both climatic variables, key hydromorphological characteristics, and, if available, trophic state characteristics will be better equipped to predict the magnitude and ecological consequences of warming in reservoirs. This understanding is essential for informing adaptive management strategies, particularly concerning water quality, reservoir stratification control, and biodiversity conservation under future climate scenarios.

CRediT authorship contribution statement

Petr Znachor: Writing - Review & Editing, Writing - Original Draft, Validation, Supervision, Project Administration, Methodology, Investigation, Funding Acquisition, Formal Analysis, Data Curation, Conceptualization. **Dušan Kosour:** Validation, Data Curation. **Luděk Rederer:** Validation, Data Curation. **Václav Koza:** Validation, Data Curation. **Vojtěch Kolář:** Writing - Review & Editing, Writing - Original Draft, Formal Analysis. **Jiří Nedoma:** Writing - Review & Editing, Writing - Original Draft, Validation, Methodology, Investigation, Formal Analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Petr Znachor reports financial support was provided by Czech Science Foundation.

Acknowledgements

We gratefully acknowledge the water authorities of the Elbe, Morava, and Vltava River basins for providing the data used in this study. The study was supported by the Czech Science Foundation, Project No. 22-33245S. We also thank the three anonymous reviewers for their constructive and insightful comments, which significantly improved the quality of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ese.2025.100631.

References

[1] R.I. Woolway, B.M. Kraemer, J.D. Lenters, C.J. Merchant, C.M. O'Reilly, S. Sharma, Global Lake responses to climate change, Nat. Rev. Earth Environ. 1 (2020) 388–403, https://doi.org/10.1038/s43017-020-0067-5.
[2] R.I. Woolway, S. Sharma, J.P. Smol, Lakes in hot water: the impacts of a changing climate on aquatic ecosystems, Bioscience 72 (2022) 1050–1061, https://doi.org/10.1093/biosci/biac052.
[3] C.M. O'Reilly, S. Sharma, D.K. Gray, S.E. Hampton, J.S. Read, R.J. Rowley, P. Schneider, J.D. Lenters, P.B. McIntyre, B.M. Kraemer, G.A. Weyhenmeyer, D. Straile, B. Dong, R. Adrian, M.G. Allan, O. Anneville, L. Arvola, J. Austin, J. L. Bailey, J.S. Baron, J.D. Brookes, E. de Eyto, M.T. Dokulil, D.P. Hamilton, K. Havens, A.L. Hetherington, S.N. Higgins, S. Hook, L.R. Izmest'eva, K.D. Jöhnk, K. Kangur, P. Kasprzak, M. Kumagai, E. Kuusisto, G. Leshkevich, D. M. Livingstone, S. MacIntyre, L. May, J.M. Melack, D.C. Müller-Navarra, M. Naumenko, P. Nõges, T. Nõges, R.P. North, P.-D. Plisnier, A. Rigosi, A. Rimmer, M. Rogora, L.G. Rudstam, J.A. Rusak, N.R. Samal, D.E. Schindler, G. Schladow, M. Schmid, S.R. Schmidt, E.A. Silow, M.E. Soylu, K. Teubner, P. Verburg, A. Voutilainen, A. Watkinson, C.E. Williamson, G. Zhang, Rapid and highly variable warming of lake surface waters around the globe, Geophys. Res. Lett. 42 (2015) 10773–10781, https://doi.org/10.1002/2015GL066235.
[4] S. Piccolroaz, R.I. Woolway, C.J. Merchant, Global reconstruction of twentieth century lake surface water temperature reveals different warming trends depending on the climatic zone, Clim. Change 160 (2020) 427–442, https://doi.org/10.1007/s10584-020-02663-z.
[5] Y. Tong, L. Feng, X. Wang, X. Pi, W. Xu, R.I. Woolway, Global lakes are warming slower than surface air temperature due to accelerated evaporation, Nat. Water. 1 (2023) 929–940, https://doi.org/10.1038/s44221-023-00148-8.
[6] R.I. Woolway, C.J. Merchant, Intralake heterogeneity of thermal responses to climate change: a study of large northern hemisphere Lakes, J. Geophys. Res. Atmos. 123 (2018) 3087–3098, https://doi.org/10.1002/2017JD027661.
[7] M.T. Dokulil, Increasing maximum lake surface temperature under climate change, Clim. Change 165 (2021) 56, https://doi.org/10.1007/s10584-021-03085-1.
[8] L. Chen, Y. Luo, K. Yang, S. Zhu, Y. Guan, Z. Zhou, G. Liu, H. Chen, A. Li, R. I. Woolway, Glacier meltwater modulation of lake warming trends in China, Innov. Geosci. 3 (2025) 100147, https://doi.org/10.59717/j.xinn-geo.2025.100147.
[9] D.P. Li, Y. Luo, K. Yang, C.X. Shang, S.L. Zhu, S.Y. Peng, A.L. Li, R.X. Chen, Z. Q. Peng, X.F. Pei, Y.Y. Yin, Q.Q. Wang, C.Q. Peng, H. Wei, Effects of climate change and urbanization on spatiotemporal variations of lake surface water temperature, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 17 (2024) 19955–19971, https://doi.org/10.1109/JSTARS.2024.3487623.
[10] L.A. Winslow, J.S. Read, G.J.A. Hansen, K.C. Rose, D.M. Robertson, Seasonality of change: summer warming rates do not fully represent effects of climate change on lake temperatures, Limnol. Oceanogr. 62 (2017) 2168–2178, https://doi.org/10.1002/lno.10557.
[11] R.I. Woolway, M.T. Dokulil, W. Marszelewski, M. Schmid, D. Bouffard, C. J. Merchant, Warming of central european Lakes and their response to the 1980s climate regime shift, Clim. Change 142 (2017) 505–520, https://doi.org/10.1007/s10584-017-1966-4.
[12] L. Huang, R.I. Woolway, A. Timmermann, S.-S. Lee, K.B. Rodgers, R. Yamaguchi, Emergence of lake conditions that exceed natural temperature variability, Nat. Geosci. 17 (2024) 763–769, https://doi.org/10.1038/s41561-024-01491-5.
[13] S.C. Maberly, R.A. O'Donnell, R.I. Woolway, M.E.J. Cutler, M. Gong, I.D. Jones, C.J. Merchant, C.A. Miller, E. Politi, E.M. Scott, S.J. Thackeray, A.N. Tyler, Global Lake thermal regions shift under climate change, Nat. Commun. 11 (2020) 1232, https://doi.org/10.1038/s41467-020-15108-z.
[14] T. Shatwell, W. Thiery, G. Kirillin, Future projections of temperature and mixing regime of European temperate lakes, Hydrol. Earth Syst. Sci. 23 (2019) 1533–1551, https://doi.org/10.5194/hess-23-1533-2019.
[15] Z. Xu, F. Huang, Q. Liu, C. Fu, Global pattern of historical and future changes in rapid temperature variability, Environ. Res. Lett. 15 (2020) 124073, https://doi.org/10.1088/1748-9326/abccf3.
[16] X. Zhou, Q. Wang, T. Yang, Decreases in days with sudden day-to-day temperature change in the warming world, Global Planet. Change 192 (2020) 103239, https://doi.org/10.1016/j.gloplacha.2020.103239.
[17] W.A. Gough, Day-to-day temperature variability: higher-order moments and links to the synoptic-scale, Theor. Appl. Climatol. 94 (2008) 97–105, https://doi.org/10.1007/s00704-007-0346-9.
[18] B.Y. Tam, W.A. Gough, Examining past temperature variability in moosonee, thunder Bay, and Toronto, Ontario, Canada through a day-to-day variability framework, Theor. Appl. Climatol. 110 (2012) 103–113, https://doi.org/10.1007/s00704-012-0622-1.
[19] H.W. Rust, T. Kruschke, A. Dobler, M. Fischer, U. Ulbrich, Discontinuous daily temperatures in the WATCH forcing datasets, J. Hydrometeorol. 16 (2015) 465–472, https://doi.org/10.1175/JHM-D-14-0123.1.
[20] Z. Xu, F. Huang, Q. Liu, C. Fu, Global pattern of historical and future changes in rapid temperature variability, Environ. Res. Lett. 15 (2020) 124073, https://doi.org/10.1088/1748-9326/abccf3.
[21] W.A. Gough, B. Shi, Impact of coastalization on day-to-day temperature variability along China's east coast, J. Coast Res. 36 (2020) 451–456, https://doi.org/10.2112/JCOASTRES-D-19-00167.1.
[22] M. Novikmec, M. Svitok, D. Kočický, F. Šporka, P. Bitušík, Surface water temperature and ice cover of tatra Mountains lakes depend on altitude, topographic shading, and bathymetry, Arct. Antarct. Alp. Res. 45 (2013) 77–87, https://doi.org/10.1657/1938-4246-45.1.77.
[23] P. Zahradníček, R. Brázdil, P. Štěpánek, M. Trnka, Reflections of global warming in trends of temperature characteristics in the Czech Republic, 1961–2019, Int. J. Climatol. 41 (2020) 1211–1229, https://doi.org/10.1002/joc.6791.
[24] P. Zahradníček, R. Brázdil, J. Řehoř, O. Lhotka, P. Dobrovolný, P. Štěpánek, Temperature extremes and circulation types in the Czech Republic, 1961–2020, Int. J. Climatol. 42 (2021) 4808–4829, https://doi.org/10.1002/joc.7505.
[25] M. Almeida, S. Zhu, R.M. Cardoso, P.M.M. Soares, P. Coelho, Evaluating the effects of climate-induced heatwaves on the thermal dynamics and water quality of a deep reservoir in Portugal, J. Hydrol. Reg. Stud. 60 (2025) 102601, https://doi.org/10.1016/j.ejrh.2025.102601.
[26] P. Znachor, J. Nedoma, J. Hejzlar, J. Seďa, J. Kopáček, D. Boukal, T. Mrkvička, Multiple long-term trends and trend reversals dominate environmental conditions in a man-made freshwater reservoir, Sci. Total Environ. 624 (2018) 1627–1638, https://doi.org/10.1016/j.scitotenv.2017.12.061.
[27] J. Kopáček, S. Grill, J. Hejzlar, P. Porcal, J. Turek, Tree dieback and subsequent changes in water quality accelerated the climate-related warming of a central European forest lake, J. Water Clim. Change 15 (2024) 127–138, https://doi.org/10.2166/wcc.2023.581.
[28] R. Wang, W. Dong, J. Sun, M. Sojka, M. Ptak, S. Zhu, Long-term trends of lake surface water temperatures in lowland Polish temperate lakes, Atmosphere 16 (2025) 120, https://doi.org/10.3390/atmos16020120.
[29] R.M. O'Brien, A caution regarding rules of thumb for variance inflation factors, Qual. Quantity 41 (2007) 673–690, https://doi.org/10.1007/s11135-006-9018-6.
[30] R Core Team, R: a Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2024.
[31] F. Hartig, DHARMa: residual diagnostics for hierarchical (multilevel/mixed) regression models, R package (2020).
[32] B. Bolker, R development core team, bbmle: tools for general maximum likelihood estimation, R package (2020).
[33] D. Lüdecke, Performance: an R package for assessment, comparison and testing of statistical models, J. Open Source Softw. 6 (2021) 3139, https://doi.org/10.21105/joss.03139.
[34] D. Lüdecke, Ggeffects: tidy data frames of marginal effects from regression

models, J. Open Source Softw. 3 (2018) 772, https://doi.org/10.21105/joss.00772.
[35] S.R. Hanna, G.A. Briggs, R.P. Hosker, Handbook on Atmospheric Diffusion, U.S. Department of Energy, Technical Information Center, 1982. DOE/TIC-11223.
[36] H. Li, J. Sun, Q. Zhou, M. Sojka, M. Ptak, Y. Luo, S. Wu, S. Zhu, V.R. Tóth, 150-year daily data (1870–2021) in lakes and rivers reveals intensifying surface water warming and heatwaves in the Pannonian ecoregion (Hungary), J. Hydrol. Reg. Stud. 56 (2024) 101985, https://doi.org/10.1016/j.ejrh.2024.101985.
[37] R. Noori, R.I. Woolway, M. Saari, M. Pulkkanen, B. Kløve, Six decades of thermal change in a pristine Lake situated north of the Arctic circle, Water Resour. Res. 58 (2022) e2021WR031543, https://doi.org/10.1029/2021WR031543.
[38] R. Noori, S.M. Bateni, M. Saari, M. Almazroui, A.T. Haghighi, Strong warming rates in the surface and bottom layers of a boreal Lake: results from approximately six decades of measurements (1964–2020), Earth Space Sci. 9 (2022) e2021EA001973, https://doi.org/10.1029/2021EA001973.
[39] R.I. Woolway, S. Sharma, G.A. Weyhenmeyer, A. Debolskiy, M. Golub, D. Mercado-Bettín, M. Perroud, V. Stepanenko, Z. Tan, L. Grant, R. Ladwig, J. Mesman, T.N. Moore, T. Shatwell, I. Vanderkelen, J.A. Austin, C.L. DeGasperi, M. Dokulil, S. La Fuente, E.B. Mackay, S.G. Schladow, S. Watanabe, R. Marcé, D. C. Pierson, W. Thiery, E. Jennings, Phenological shifts in lake stratification under climate change, Nat. Commun. 12 (2021) 1–11, https://doi.org/10.1038/s41467-021-22657-4.
[40] S.F. Jane, G.J.A. Hansen, B.M. Kraemer, P.R. Leavitt, J.L. Mincer, R.L. North, R. M. Pilla, J.T. Stetler, C.E. Williamson, R.I. Woolway, L. Arvola, S. Chandra, C. L. DeGasperi, L. Diemer, J. Dunalska, O. Erina, G. Flaim, H.-P. Grossart, K. D. Hambright, C. Hein, J. Hejzlar, L.L. Janus, J.-P. Jenny, J.R. Jones, L.B. Knoll, B. Leoni, E. Mackay, S.-I.S. Matsuzaki, C. McBride, D.C. Müller-Navarra, A. M. Paterson, D. Pierson, M. Rogora, J.A. Rusak, S. Sadro, E. Saulnier-Talbot, M. Schmid, R. Sommaruga, W. Thiery, P. Verburg, K.C. Weathers, G. A. Weyhenmeyer, K. Yokota, K.C. Rose, Widespread deoxygenation of temperate lakes, Nature 594 (2021) 66–70, https://doi.org/10.1038/s41586-021-03550-y.
[41] A.M. Michalak, Study role of climate change in extreme threats to water quality, Nature 535 (2016) 349–350, https://doi.org/10.1038/535349a.
[42] H.W. Paerl, J. Huisman, Blooms like it hot, Science (2008), https://doi.org/10.1126/science.1155398.
[43] R.C. Lathrop, P. Kasprzak, M. Tarvainen, A.-M. Ventelä, T. Keskinen, R. Koschel, D.M. Robertson, Seasonal epilimnetic temperature patterns and trends in a suite of lakes from Wisconsin, Germany, and Finland, Inland Waters 9 (2019) 471–488, https://doi.org/10.1080/20442041.2019.1637682.
[44] K. Stefanidis, G. Varlas, Trends of lake temperature, mixing depth and ice cover thickness of European lakes during the last four decades, Sci. Total Environ. 830 (2022) 154709, https://doi.org/10.1016/j.scitotenv.2022.154709.
[45] B.M. Kraemer, O. Anneville, S. Chandra, M. Dix, E. Kuusisto, D.M. Livingstone, A. Rimmer, S.G. Schladow, E. Silow, L.M. Sitoki, R. Tamatamah, Y. Vadeboncoeur, P.B. McIntyre, Morphometry and average temperature affect lake stratification responses to climate change, Geophys. Res. Lett. 42 (2015) 4981–4988, https://doi.org/10.1002/2015GL064097.
[46] R.I. Woolway, C.J. Merchant, Amplified surface temperature response of cold, deep lakes to climate warming, Sci. Rep. 7 (2017) 4130, https://doi.org/10.1038/s41598-017-04058-0.
[47] J.S. Read, D.P. Hamilton, A.R. Desai, K.C. Rose, S. MacIntyre, C.H. Wu, Lake-size dependency of wind shear and convection as controls on gas exchange, Geophys. Res. Lett. 41 (2014) 527–533, https://doi.org/10.1029/2012GL051886.
[48] G. Kirillin, T. Shatwell, Generalized scaling of seasonal thermal stratification in lakes, Earth Sci. Rev. 161 (2016) 179–190, https://doi.org/10.1016/j.earscirev.2016.08.008.
[49] A. Nielsen, D. Trolle, M. Søndergaard, T.L. Lauridsen, R. Bjerring, J.E. Olesen, E. Jeppesen, Watershed land use effects on lake water quality in Denmark, Ecol. Appl. 22 (2012) 1187–1200, https://doi.org/10.1890/11-1831.1.
[50] R. Adrian, C.M. O'Reilly, H. Zagarese, S.B. Baines, D.O. Hessen, W. Keller, D. M. Livingstone, R. Sommaruga, D. Straile, E. Van Donk, G.A. Weyhenmeyer, M. Winder, Lakes as sentinels of climate change, Limnol. Oceanogr. 54 (2009) 2283–2297, https://doi.org/10.4319/lo.2009.54.6_part_2.2283.
[51] R.I. Woolway, C.J. Merchant, J. Van Den Hoek, C. Azorin-Molina, P. Nõges, A. Laas, E.B. Mackay, I.D. Jones, Northern hemisphere atmospheric stilling accelerates Lake thermal responses to a warming world, Geophys. Res. Lett. 46 (2019) 11983–11992, https://doi.org/10.1029/2019GL082752.
[52] K. Yang, Z. Peng, Y. Luo, C. Shang, The heat exchange process between surface water and near-surface atmosphere in the front of the three gorges dam, Int. J. Appl. Earth Obs. Geoinf. 102 (2021) 102372, https://doi.org/10.1016/j.jag.2021.102372.
[53] P. Jurajda, Z. Adámek, Z. Valová, M. Janáč, K. Roche, Fish community and fisheries management of Brno reservoir following revitalisation measures, Folia Zool. 64 (2015) 112–122, https://doi.org/10.25225/fozo.v64.i2.a4.2015.
[54] Z. Bešťáková, J. Kyselý, O. Lhotka, M. Heilig, J. Eitzinger, Warm-season drying across Europe and its links to atmospheric circulation, Earth Space Sci. 11 (2024) e2023EA003434, https://doi.org/10.1029/2023EA003434.
[55] M. Ptak, T. Amnuaylojaroen, M. Sojka, Seven decades of surface temperature changes in central European lakes: what is next? Resources 13 (2024) 149, https://doi.org/10.3390/resources13110149.
[56] M. Ionita, V. Nagavciuc, R. Kumar, O. Rakovec, On the curious case of the recent decade, mid-spring precipitation deficit in central Europe, NPJ Clim. Atmos. Sci. 3 (2020) 1–10, https://doi.org/10.1038/s41612-020-00153-8.
[57] Q. Tang, G. Leng, P.Y. Groisman, European hot summers associated with a reduction of cloudiness, J. Clim. 25 (2012) 3637–3644, https://doi.org/10.1175/JCLI-D-12-00040.1.
[58] G.A. Weyhenmeyer, Y.T. Prairie, L.J. Tranvik, Browning of boreal freshwaters linked to increased iron concentrations and DOC from the landscape, Proc. Natl. Acad. Sci. USA 111 (2014) 11235–11240, https://doi.org/10.1371/journal.pone.0106357.
[59] C.E. Williamson, E.P. Overholt, R.M. Pilla, T.H. Leach, J.A. Brentrup, L.B. Knoll, E.M. Mette, R.E. Moeller, Ecological consequences of long-term browning in lakes, Sci. Rep. 5 (2015) 1–10, https://doi.org/10.1038/srep18666.
[60] J.P. Doubek, C.C. Carey, N.K. Ward, The extent and variability of storm-induced temperature changes in lakes, Limnol. Oceanogr. 66 (2021) 311–325, https://doi.org/10.1002/lno.11739.
[61] J. Imberger, J.C. Patterson, Physical limnology, Adv. Appl. Mech. 27 (1990) 303–475, https://doi.org/10.1016/S0065-2156(08)70199-6.
[62] J.D. Stockwell, J.P. Doubek, R. Adrian, O. Anneville, C.C. Carey, L. Carvalho, L. N. De Senerpont Domis, G. Dur, M.A. Frassl, P. Grossart, B.W. Ibelings, M. J. Lajeunesse, A.M. Lewandowska, M.E. Llames, I.S. Matsuzaki, E.R. Nodine, P. Nõges, V.P. Patil, F. Pomati, K. Rinke, L.G. Rudstam, J.A. Rusak, N. Salmaso, C. T. Seltmann, D. Straile, S.J. Thackeray, W. Thiery, P. Urrutia-Cordero, P. Venail, P. Verburg, R.I. Woolway, T. Zohary, M.R. Andersen, R. Bhattacharya, J. Hejzlar, N. Janatain, A.T.N.K. Kpodonu, T.J. Williamson, H.L. Wilson, Storm impacts on phytoplankton community dynamics in lakes, Glob. Change Biol. 26 (2020) 2756–2784, https://doi.org/10.1111/gcb.15033.
[63] P. Znachor, E. Zapomělová, K. Řeháková, J. Nedoma, K. Šimek, The effect of extreme rainfall on summer succession and vertical distribution of phytoplankton in a lacustrine part of a eutrophic reservoir, Aquat. Sci. 70 (2008) 77–86, https://doi.org/10.1007/s00027-007-7033-x.
[64] V. Tran-Khac, J.P. Doubek, V. Patil, J.D. Stockwell, R. Adrian, C.W. Chang, G. Dur, A. Lewandowska, J.A. Rusak, N. Salmaso, D. Straile, S.J. Thackeray, P. Venail, R. Bhattacharya, J. Brentrup, R. Bruel, H. Feuchtmayr, M.O. Gessner, H.P. Grossart, B.W. Ibelings, S. Jacquet, S. MacIntyre, S.I.S. Matsuzaki, E. Nodine, P. Noges, L.G. Rudstam, F. Soulignac, P. Verburg, P. Znachor, T. Zohary, O. Anneville, Using long-term ecological datasets to unravel the impacts of short-term meteorological disturbances on phytoplankton communities, Freshw. Biol. 70 (2025) e70023, https://doi.org/10.1111/fwb.70023.
[65] J. Zhou, P.R. Leavitt, K.C. Rose, X. Wang, K. Shi, B. Qin, Controls of thermal response of temperate lakes to atmospheric warming, Nat. Commun. 14 (2023) 6503, https://doi.org/10.1038/s41467-023-42262-x.
[66] P. Znachor, J. Hejzlar, J. Vrba, J. Nedoma, J. Seďa, K. Šimek, J. Komárková, Brief history of long-term ecological research into aquatic ecosystems and their catchments in the Czech Republic: part I – manmade reservoirs, Czech LTER, Institut. Hydrobiol. Biol. Centre CAS (2016) 80. ISBN: 978-80-86668-38-3.
[67] P. Znachor, J. Nedoma, J. Hejzlar, J. Seďa, J. Komárková, V. Kolář, T. Mrkvička, D.S. Boukal, Changing environmental conditions underpin long-term patterns of phytoplankton in a freshwater reservoir, Sci. Total Environ. 710 (2020) 135626, https://doi.org/10.1016/j.scitotenv.2019.135626.
[68] B.M. Kraemer, R.M. Pilla, R.I. Woolway, O. Anneville, S. Ban, W. Colom-Montero, S.P. Devlin, M.T. Dokulil, E.E. Gaiser, K.D. Hambright, D.O. Hessen, S. N. Higgins, K.D. Jöhnk, W. Keller, L.B. Knoll, P.R. Leavitt, F. Lepori, M.S. Luger, S.C. Maberly, D.C. Müller-Navarra, A.M. Paterson, D.C. Pierson, D. C. Richardson, M. Rogora, J.A. Rusak, S. Sadro, N. Salmaso, M. Schmid, E. A. Silow, R. Sommaruga, J.A.A. Stelzer, D. Straile, W. Thiery, M.A. Timofeyev, P. Verburg, G.A. Weyhenmeyer, R. Adrian, Climate change drives widespread shifts in lake thermal habitat, Nat. Clim. Change 11 (2021) 521–529, https://doi.org/10.1038/s41558-021-01060-3.
[69] IPCC, Climate change 2021: the physical science Basis. Contribution of working group I to the sixth assessment report. https://doi.org/10.1017/9781009157896, 2021.