Climatic Change (2021) 166: 21
https://doi.org/10.1007/s10584-021-03124-x

Climate change enhances deepwater warming of subtropical reservoirs: evidence from hydrodynamic modelling

Laura Melo Vieira Soares[1] · **Maria do Carmo Calijuri**[1] · **Talita Fernanda das Graças Silva**[2] · **Evlyn Marcia Leão de Moraes Novo**[3]

Received: 14 September 2020 / Accepted: 17 May 2021 / Published online: 25 May 2021
© The Author(s), under exclusive licence to Springer Nature B.V. 2021

Abstract
Lake surface warming and thermal responses to climate change have been widely reported, especially in temperate regions. Evidence of reservoir response in low latitudes is still limited. In this study, the vertical profile of water temperature in the Barra Bonita Reservoir (Brazil) is simulated using the one-dimensional General Lake Model (GLM), calibrated, and validated using in-situ data. Water temperature and reservoir hydrodynamics are simulated over 26 years (1993–2018) to investigate warming trends, seasonal patterns, Schmidt stability, and the number of stratified days per year. Results indicate that the reservoir has experienced significant warming since 1993 related to increasing air temperature and decreasing wind speed. Water temperature increases (p value <0.001) from the surface (+ 1.02 °C per decade) to the bottom (0.33 °C per decade). Higher warming rates are detected during the dry and cold season. Significant increasing trends are found for Schmidt stability and in the number of stratified days per year. Deepwater warming is directly related to increasing air temperature and frequent mixing episodes which transfer heat from surface to bottom waters. A deep outlet structure and an artificially controlled water level may enhance deepwater warming during the dry season. Our findings contribute to the understanding of subtropical reservoirs' response to climate change and help to guide planning strategies for ensuring the security of water storage and ecosystem services they provide.

Keywords Hydrodynamics · Climate forcing · Thermal structure · Temporal trends · Sen's estimator of slope · General Lake Model (GLM)

✉ Laura Melo Vieira Soares
lauramvsoares@gmail.com

Extended author information available on the last page of the article

1 Introduction

Several studies have assessed the impact of climate change on the thermal structure of lakes which are recognized as sentinels of such changes due to their sensitivity to atmospheric conditions and their ability to integrate the effects of climate-driven changes occurring within the catchment (Adrian et al. 2009). The increase in lake surface temperature, primarily driven by rises in air temperature, was the most frequent finding (Woolway and Merchant 2019). In addition to warming, thermal dynamic responses have also been widely reported, such as the stronger (Sahoo et al. 2016) and longer (Magee et al. 2016) thermal stratification, and shallower thermocline depth (Bayer et al. 2013). Reservoirs also integrate atmospheric and catchment, thus ultimately capturing climate signals (Williamson et al. 2009). However, given their largely anthropogenically controlled hydrology, climate-related responses are influenced by specific features of individual systems.

Reservoirs play an important role in controlling and managing water resources. They have been built over the past decades, reaching about 50,000 large reservoirs worldwide (Lehner et al. 2011). Their global expansion has increased access to drinking water, irrigation, navigation, flood control, and hydropower generation. Moreover, similar to lakes, reservoirs provide key ecosystem services of supporting, provisioning, regulating, and cultural services (Janssen et al. 2020). Although the lacustrine zone of reservoirs shares several similarities with natural lakes, they differ in attributes regarding their catchment, waterbody, management, and geographic distribution, leading to differences in ecosystem functioning (Hayes et al. 2017).

In Brazil, the National Dam Safety Information System registered more than 24,000 reservoirs until 2017, from which 69% have irrigation, livestock watering, or fish breeding as the main purpose (ANA 2018a). In this context, understanding how reservoirs respond to climate change and their interactions with meteorological drivers are of paramount importance for ensuring the security of water storage, ecological balance, goods, and ecosystem services they provide to society. Although recent studies investigated climate impacts on reservoirs (e.g. Zhang et al. 2015; Lewis Jr. et al. 2019), available information for lentic ecosystems in the tropics is still limited (Ramírez et al. 2020). As a result, while there is sufficient evidence on the effects of climate change over lakes under a temperate climate, a further understanding of how subtropical reservoirs respond is still required.

Accordingly, this study investigates the thermal changes of a subtropical reservoir over 26 years. Considering the low-frequency of field measurements, a one-dimensional hydrodynamic model was applied to simulate the reservoir's thermal structure aiming (1) to compute water column temperature trends, (2) to investigate trends in stratification strength and duration based on the Schmidt stability and the number of stratified days per year, (3) to describe the specific mechanisms of reservoir's internal response to climate forcing, and (4) to envisage potential driving factors explaining thermal changes. Considering a global boom in dam construction (Zarfl et al. 2014), understanding the mechanisms that govern reservoir response to climate change is becoming increasingly urgent.

2 Material and methods

2.1 Study site

The subtropical Barra Bonita Reservoir is a medium-size water body situated in southeast Brazil (22° 28′ 16″ S, 48° 33′ 27″ W) at 451 m above sea level. The reservoir impounds the waters of the Tietê River, the Piracicaba River, and several small creeks (Fig. 1). The only reservoir outflow is the Tietê River with a mean annual discharge of 405 m^3 s^{-1}. It was built in the 1960s to meet hydroelectric power demands and currently is also used for navigation, tourism, irrigation, and aquaculture. The reservoir has a maximum depth of 23.5 m and a mean depth of 10.2 m. Its mixing regime is typically polymictic with full mixing events alternating with short periods (around 5 days) of thermal stratification throughout the year (Soares et al. 2020).

Barra Bonita Reservoir differs from a typical lake in several ways that lead to differences in ecosystem functioning (Hayes et al. 2017): (1) long and narrow morphometry with a high degree of irregularity of the shoreline (see Fig. 1); (2) storage of a large volume of water (3.6×10^9 m^3) and short hydraulic residence time (0.28 years); (3) an outlet structure controls the water level, resulting in a mean annual level fluctuation of about 5.0 m; (4) a large ratio of the catchment area (32,300 km^2) to reservoir surface area (310 km^2) and; (5) it is predominantly fed by surface water from higher order streams.

Barra Bonita reservoir is located in a catchment area extensively occupied by agriculture (62%, mostly sugarcane), urban areas (12%), pasture (5%), vegetation (20%), and water bodies (1%) (IBGE 2018). Its tributaries receive nutrient input from agricultural areas and domestic and industrial effluent discharges from large urban centres, including São Paulo Metropolitan Region. These are the key factors contributing to the degradation of the water quality causing its super-eutrophic status, shallow Secchi depth, frequent hypoxic events, and Cyanobacteria blooms (CETESB 2019).

The annual mean air temperature is 20.7 °C, the mean monthly air temperature varies from 17.1 °C in June to 23.1 °C in February. The mean total annual precipitation is 1525 mm mostly occurring from October to March (mean values computed from 1993 to 2018, INMET 2019).

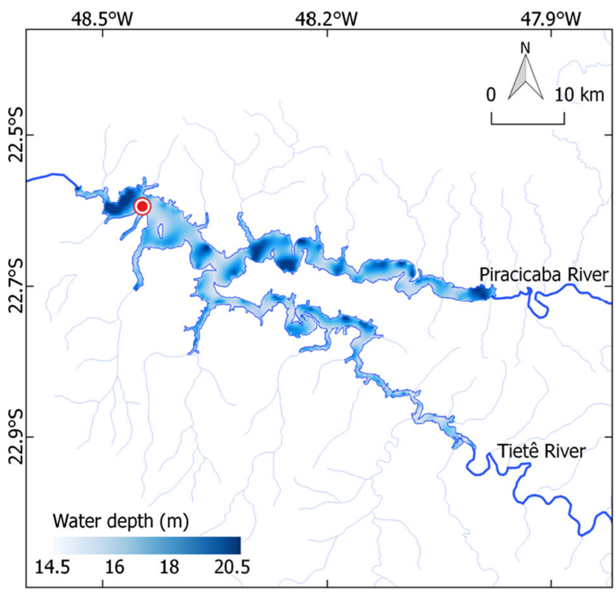

Fig. 1 The Barra Bonita Reservoir, its bathymetry, and tributaries. The red circle indicates the monitoring station

2.2 Model description

The one-dimensional General Lake Model (GLM) version 2.2.0 (Hipsey et al. 2019) was used to simulate the hydrodynamics of the Barra Bonita Reservoir. GLM was developed in 2012 based on approaches from previous model platforms (Imberger and Patterson 1990; Hamilton and Schladow 1997). A series of improvements were incorporated since then and so GLM has been applied to a variety of lentic environments (Read et al. 2014; Bueche et al. 2017; Snortheim et al. 2017; Bruce et al. 2018). It is an open-source code, which is available for free.

GLM simulates the vertical profiles of temperature, salinity, and density in lentic water bodies. The model adopts the fundamental assumption of 1D models, i.e., the mixing within the lake results from processes acting in the vertical and gradients in the horizontal plane are much smaller and have minimal impact on the vertical transport of energy and mass. The 1D assumption was validated for the Barra Bonita Reservoir in a previous study (Soares et al. 2020) through the computation of the Wedderburn number which was much higher than one. A flexible Lagrangian layer structure is used to discretize the water column into horizontal layers to simulate the vertical variation in water properties. This approach defines each layer as a “control volume” with homogeneous density computed from the simulated salinity and temperature. Each layer can change its thickness by contraction and expansion in response to inflows, outflows, mixing with adjacent layers, and surface mass fluxes.

Thermal mixing processes are simulated using the water balance and energy budget computed at every time step. Within the lake domain, the model solves the water balance regarding several water fluxes, including surface mass fluxes (evaporation and rainfall), inflows (surface and submerged inflows), and outflows (withdrawals, overflow, and seepage). GLM adopts a dynamic balance between kinetic and potential energy. On one hand, during stratification periods, as the water density gradient increases, potential energy is stored. Turbulent kinetic energy, on the other hand, is provided by wind stirring, convective overturn, shear production between layers, and Kelvin–Helmholtz billowing. When density instabilities occur between adjacent layers or when sufficient turbulent kinetic energy becomes available, the stable density gradients disrupt, and then layers merge, thereby accounting for the mixing process.

GLM requires the reservoir bathymetry, meteorological data (air temperature, wind speed, air relative humidity, rainfall, shortwave radiation, and longwave radiation or cloud cover), inflow (discharge, water temperature, and salinity), and outflow (discharge) data.

2.3 Required data for hydrodynamic modelling

Five monitoring stations provided meteorological, hydrological, and limnological data used in this work (Table S1). Reservoir’s hypsographic curve was extracted from a 1-m resolution bathymetrical survey provided by Corrêa Filho et al. (2003). The model uses the information to internally compute the depth-area-volume relationship as the volume of the Lagrangian layers changes.

Daily meteorological data on air temperature, wind speed, air relative humidity, rainfall, and cloud cover were provided by São Carlos station, and daily insolation data were provided by São Simão station. Both stations are operated by the National Institute of Meteorology (INMET 2020) and they are located 80 km and 148 km, respectively, northeast of the reservoir. Occasional missing data (3–14% of gaps for each variable) were replaced by linear interpolation. Although the insolation data were obtained from a different meteorological station, the location of both stations is subject to the same isocurve of daily insolation (Tiba 2000). Solar radiation was estimated from insolation using the Angströn-Prescott method (Angstrom 1924; Prescott 1940) and was subjected to a sine wave disaggregation by GLM to obtain a sub-daily light time-series. Cloud cover data were used for predicting longwave radiation.

Daily inflow and outflow discharges were provided by the National Water Agency (ANA 2019). A small number of missing values of inflow discharges (0.03% of gaps) were filled by linear interpolation. No missing values occurred in the outflow discharge time-series.

Inflow temperature and electrical conductivity were obtained from a fluviometric station (ANA 2019) operated by the Environmental Company of São Paulo State (CETESB) at a bimonthly frequency in the Tietê River from 1999 to 2010. As the model requires daily inflow temperature, linear correlation analyses between inflow temperature and several meteorological variables were investigated. The highest linear correlation was found between inflow temperature and mean air temperature ($r = 0.78$, p value <0.001; Fig. S1). Hence, bimonthly inflow temperature was converted into the daily frequency, following the same procedure found in previous studies (Hornung 2002; Rolighed et al. 2016; He et al. 2019; Silva et al. 2019). Considering that direct tributaries contribute to a small fraction of the total annual inflow, variations in their water temperature were assumed to have a negligible impact on the Barra Bonita Reservoir's thermal dynamics. The difference between water temperature in the Tietê River and Piracicaba River is not statistically significant (Mann-Whitney U test, p value = 0.08). Therefore, the Tietê River water temperature was assumed to be representative of all inflows. Electrical conductivity data were used to estimate inflow salinity according to Hornung (2002). Due to the small salinity content in addition to its low influence in freshwater systems, salinity was assumed to be constant and equal to its average value (0.1 g kg^{-1}).

Additionally, GLM requires in-lake temperature, salinity, and water level for both model calibration and validation, as well as for setting its initial conditions. Surface water temperature and electrical conductivity in the Barra Bonita Reservoir has been reliably monitored since 2003, the Secchi depth since 2005, and water temperature measurements have been carried out at 1-m intervals from the surface to the bottom since 2008. All measurements are performed bi-monthly at a central location in the reservoir by CETESB (2019; see Fig. 1). The reservoir's daily water level has been measured since 2003 by ANA (2018b). The abovementioned monitoring stations are presented in Fig. S2 and the methodological steps followed in this study (to be detailed in the following sections) are summarized in Fig. S3.

2.4 Model setup and sensitivity analysis

GLM was set to simulate the Barra Bonita Reservoir water temperature at a daily step in response to the daily meteorological input data. A baseline simulation was run using the input data previously described and initial parameter values (Table S2) based on Hipsey et al. (2014). The simulation period was from 22nd January 2003, the first day with field measurements, to 31st December 2018. The light extinction coefficient ($K_W = 1.3$ m^{-1}) was determined from the mean value of the Secchi depth (SD) measurements and assuming $K_W = 1.7/SD$ (Poole and Atkins 1929). The initial conditions of water temperature in the reservoir came from in-situ water surface measurements on the first simulation day. The initial salinity was estimated from electrical conductivity measured at the water surface.

To identify the most sensitive of the eleven parameters frequently assessed in previous studies based on GLM (Table S2), a sensitivity analysis was carried out. The normalized sensitivity coefficient (SI) was computed from:

$$\mathrm{SI} = \frac{\Delta Y/Y}{\Delta X/X} \tag{1}$$

where Y is the model performance for the reference value X of the parameter, which has a variation ΔX generating a model performance variation ΔY.

For sensitivity analysis, the model performance was assessed with Root Mean Square Error (RMSE). The one-at-a-time method was adopted by increasing and decreasing the parameter initial values by 10%. All parameters presented SI < 0.05 (Fig. S4) indicating low to negligible individual influence in the model output (Bueche et al. 2019). Thus, all eleven parameters were included in the calibration procedure.

2.5 Model calibration and validation

For the calibration of water temperature and water level, a period of 5 years was simulated between the 15th of January 2008 and 31st of December 2012, the first years with field monitoring of the vertical temperature profile. Calibration was manually implemented by an iterative trial-and-error process. Employing successive simulations, the parameters were adjusted up to reaching a minimum RMSE value computed from observed and simulated data. The range for the parameters' values (Table S2) was based on previous applications of 1D models (Tanentzap et al. 2007; Weinberger and Vetter 2012; Kerimoglu and Rinke 2013; Fadel et al. 2017; Huang et al. 2017; Snortheim et al. 2017).

In GLM, hydrological and meteorological data may be adjusted through multiplicative factors which vary from 0 to 1 and will proportionally increase (or decrease) input data values. These multiplicative factors, such as wind factor or inflow factor, are commonly used in model calibration aiming at compensating uncertainties in field data, such as measurement errors, or differences between conditions around the monitoring station and conditions near the reservoir (Huang et al. 2017; Bueche et al. 2019; Soares et al. 2019). In this study, inflow and outflow factors were calibrated in the range of 0.9 to 1.1 to ensure a proper representation of the reservoir water balance. Multiplicative factors of shortwave, cloud cover, wind speed, air temperature, air relative humidity, and rainfall were also calibrated in the range of 0.7 to 1.3.

The validation of the best-fitted model used two independent datasets: the surface water temperature from the 22nd of January 2003 to 31st of December 2007 and the vertical profile of temperature from the 22nd of January 2013 to 31st of December 2018. The simulated water level was also validated for the same periods. RMSE was used as the objective function for assessing the model performance of water temperature and water level during calibration and validation periods.

2.6 Assessment of model performance

A continuous simulation was performed for 16 years, from January 2003 to December 2018 applying the calibrated parameters and multiplicative factors. The model performance was assessed through error measures calculated from simulated and observed water temperature. A warm-up period of nearly 2 months was adequate for model stabilization, which is likely related to the homogeneous temperature along the water column on the first day of simulation. This warm-up period was left out from the performance assessment to avoid uncertainties of initial conditions. The model skill test was performed by applying the summary measures (Table S3) according to Willmott (1981): mean values of observed and simulated water temperature ($\overline{O}$ and $\overline{S}$), their standard deviation (s_O and s_S), the intercept (a) and slope (b) of the least-squares linear regression, mean absolute error (MAE), and root mean square error (RMSE). Additionally, a set of four commonly used measures of model fit was applied to identify deviations from observed data, highlighting different aspects of model performance (Bennett et al. 2013): mean absolute percentage error (MAPE), Pearson correlation coefficient (r), percent bias (PBIAS), and mean bias error (MBE).

2.7 Temporal trends in the reservoir and in forcing variables

Trends in the thermal regime of the Barra Bonita Reservoir were explored using GLM simulation for the complete period of available input data, from the 1st of January 1993 to 31st of December 2018. Because field data is only available from 2003, the initial conditions of water temperature in the reservoir on the 1st of January 1993 were defined as the mean value of water temperature measured in January from 2008 to 2018 at every 1-m depth.

The assessment of the reservoir hydrodynamic behaviour used the mean water temperature at 2-m intervals over the water column, from the surface to 14 m depth, and the thermal conditions were expressed by the Schmidt stability index (Idso 1973) and the number of stratified days per year. The Schmidt stability index assesses the strength of the vertical temperature stratification and was implemented according to Read et al. (2011). The number of stratified days per year followed Lewis (2000) by computing the difference between surface and bottom temperatures higher than 2 °C.

As applied in previous studies (O' Reilly et al. 2015; Schmid and Koster 2016; Winslow et al. 2017), Theil-Sen's slope estimator (hereafter Sen's slope) was used in this study to estimate trends in the water temperature, Schmidt stability, and the number of stratified days per year, at the 0.05 significance level, considering their mean annual and monthly values. Sen's slope is a robust nonparametric method for estimating trends based on a simple linear regression where the fitted line is the median of the slopes of all lines that connect pairs of sample points (Sen 1968). Hirsch et al. (1982) adapted Sen's slope to account for seasonality in data sets. Sen's slope and significance levels were computed using the MAKESENS software v. 1.0 (Salmi et al. 2002). The non-parametric Mann-Whitney U test and its significance level were computed using the PAST software v. 3.25 (Hammer 2019) to compare the median of indicators between different time periods.

To explore the temporal trends in the forcing variables, Sen's slope was also computed for meteorological and hydrological input data (air temperature, solar radiation, cloud cover, air relative humidity, wind speed, rainfall, inflow discharge, and outflow discharge) considering the mean annual and monthly values. As the inflow temperature was obtained from the linear correlation with mean air temperature (see Section 2.3), its temporal trend was not computed to avoid duplicity with trends in air temperature.

To further explore the warming trends in water temperature, a detrended analysis of the wind speed was performed to verify whether the warming trends in the Barra Bonita Reservoir occurred regardless of the changes in wind speed. This variable was selected due to the distance between the meteorological station and the reservoir since among all variables, wind speed has the highest local dependence. The simulation was performed for wind speed individually detrended by keeping the original series for the first simulation year and adopting the monthly means of 1993 for the following years. All other input variables remained unchanged.

3 Results

3.1 Model performance

During the calibration period (2008–2012), GLM showed an RMSE of 0.80 m between the simulated and measured water level. During the validation periods (2003–2007 and 2013–2018), RMSE for the water level was 0.64 m and 0.87 m, respectively (Fig. S5). The water temperature was also well captured by the model. The mean RMSE along the vertical profile was 1.08 °C during the calibration period, 1.66 °C in the first validation period (2003–2007), and 1.07 °C in the second validation period (2013–2018). Minor positive and negative deviations between simulated and measured water temperatures were observed (Fig. S6). Mean RMSE of water temperature at every depth from the surface to the bottom (Fig. S7a) and at a monthly scale (Fig. S7b) was quite similar between calibration and validation periods. The RMSE values for water level and temperature were in agreement with the results of previous studies dealing with one-dimensional models (Vinçon-Leite et al. 2014; Fadel et al. 2017; Fenocchi et al. 2017; Bueche et al. 2019).

The metrics for model performance from January 2003 to December 2018 revealed similar results along the water column (Table S4), with values in the range of previous results reported in the literature (Bruce et al. 2018; Mi et al. 2019; Soares et al. 2019; Weber et al. 2017). The annual mean error during the 16-year simulation shows no systematic bias (Fig. 2). Further details regarding the model performance for the 2003–2018 period, as well as the contour plot of simulated water temperature can be found in Fig. S8 and Fig. S9.

3.2 Trends in water temperature and thermal conditions

Trend analysis of the simulated annual water temperature showed a consistent significant increasing trend along the whole water column. Annual warming trends varied from 1.02 °C per decade to 0.33 °C per decade at the surface and 14 m depth, respectively (Fig 3). An intra-

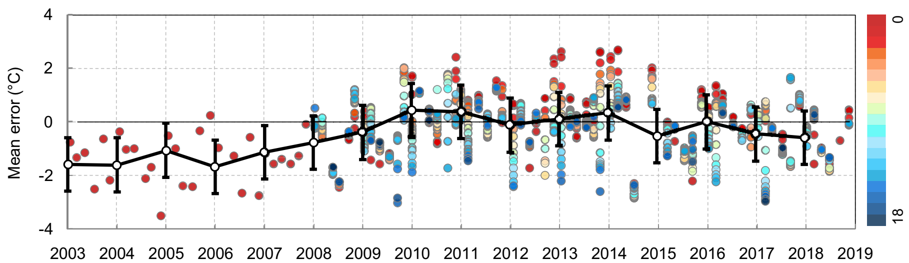

Fig. 2 The mean error between simulated and measured water temperature at different depths is represented by coloured circles during the 2003–2018 simulation period. Annual mean errors computed from all depths are represented by white circles with error bars referring to their standard deviation

annual assessment indicated consistent warming throughout the year. Monthly warming trends were significantly above zero in the entire water column from March to August during the autumn and winter seasons. The highest increase rates were observed from May to July with values above 1.05 °C per decade even in the bottom layer. A decreasing trend was observed only at 12 m and 14 m depth in a few months, yet not significant.

A graphical analysis of the simulated Schmidt stability and the number of stratified days per year indicated that both indicators did not follow a linear trend, but rather they presented a jump in the annual mean series in 2009 (Fig 4). The mean values for both indicators from 1993 to 2008 and from 2009 to 2018 were significantly different (Mann-Whitney *U* test, *p* value <0.001), with mean values of Schmidt stability and number of stratified days per year increasing from 12.3 (1993–2008) to 58.0 J m^{-2} (2009–2018) and from 2 (1993–2008) to 89 days (2009–2018), respectively.

3.3 Trends in forcing variables

Sen's slope at annual and monthly scales was computed for hydrological and meteorological data used as forcing variables in the model from 1993 to 2018. The trend analysis showed significant annual trends for air temperature (0.43 °C/decade), air relative humidity (−1.62%/decade), and rainfall (−170.05 mm/decade) (Table 1). The graphical analysis of the wind speed revealed a jump in annual mean series from 2009 (Fig. S10). The mean wind speed was significantly different (Mann-Whitney *U* test, *p* value <0.01) between 1993–2008 (mean value of 2.6 m s^{-1}) and 2009–2018 (mean value of 1.2 m s^{-1}). The remaining input variables displayed small temporal changes, in a range that might be attributed to the random interannual variability.

Monthly significant warming in air temperature (Fig. 5) was revealed mostly during the autumn and winter, with the highest increase rate in June (0.99 °C/decade). The air relative humidity significantly decreased in April, May, August, and December. The wind speed revealed a significant decrease throughout the year (*p* value <0.001). Although the annual

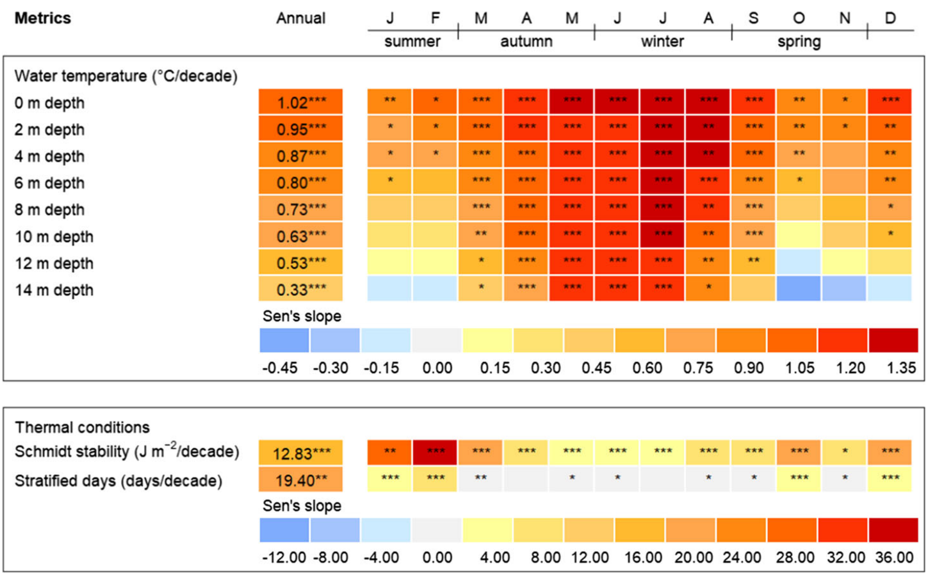

Fig. 3 Warming trends in simulated water temperature at 2-m intervals from 1993 to 2018. Note: *** for $p < 0.001$; ** for $p < 0.01$; * for $p < 0.05$

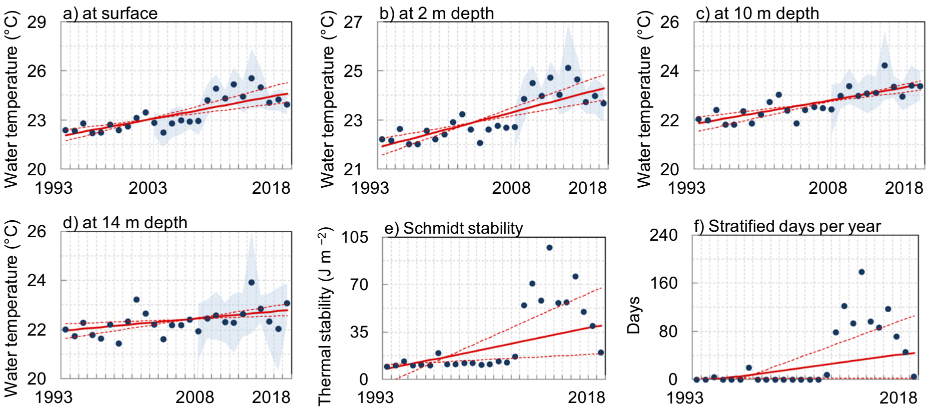

Fig. 4 Annual simulated indicators of hydrodynamic behaviour and thermal conditions (circles) for Barra Bonita Reservoir during 1993–2018, the shaded area representing their annual standard deviation, Sen's slope (solid line), and its 95% confidence interval represented by the dotted lines

rainfall trend was found to be significant, on a monthly basis, a significant trend was found only in February (−73.33 mm/decade). Finally, monthly trends in solar radiation and inflow discharge were significant only in a few months, while no significance was found for intra-annual variability in cloudiness and outflow discharge.

Indicators of hydrodynamic behaviour computed from the simulation with detrended wind speed showed positive annual warming trends of about 0.25 °C per decade, being significant during autumn and winter (Table S5, Fig. S11). The absence of a trend in wind speed resulted in a small increasing rate, although significant, for Schmidt stability at the annual scale, and not a single day during the 26 years was stratified. Then, the number of stratified days per year showed an absence of trend.

4 Discussion

4.1 Assessment of modelling performance

The modelling approach was able to quantify the trends in water temperature, which would not be possible to be computed from measured data considering the large time interval between the

Table 1 Trends in measured meteorological and hydrological forcing variables from 1993 to 2018

Forcing variable	Sen's slope
Solar radiation (W m^{-2}/decade)	0.48
Cloudiness (%/decade)	−0.03
Air temperature (°C/decade)	0.43 ***
Air relative humidity (%/decade)	−1.62*
Wind speed (m s^{-1}/decade)	−0.71***
Rainfall (mm/decade)	−170.05**
Inflow discharge (m^{3} s^{-1}/decade)	−26.24
Outflow discharge (m^{3} s^{-1}/decade)	−2.43

Note: *** for $p < 0.001$; ** for $p < 0.01$; * for $p < 0.05$

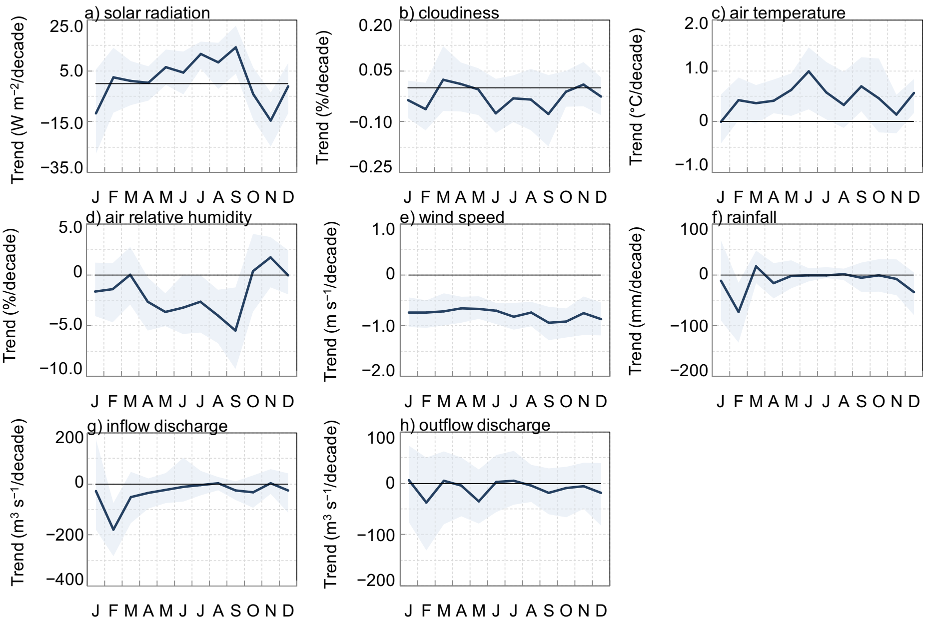

Fig. 5 Monthly trends in the forcing variables for the 1993–2018 period (solid line). The shaded areas indicate 95% confidence intervals for Sen's slopes, which means that the trend is greater (or smaller) than zero with 95% confidence if the shaded area is above (or below) the zero line for each month

water sampling measurements (every 2 months). To assess potential biases between simulated and measured thermal conditions in the reservoir, efforts were made to closely assess the model performance through several goodness-of-fit measures at every 2-m depth interval from the surface to the bottom. The GLM successfully reproduced the mass balance, the vertical temperature profile, and the intra-annual thermal behaviour of the Barra Bonita Reservoir, achieving an acceptable degree of agreement with the measured data. Thus, the model was considered reliable to reproduce water temperature dynamics from 1993 to 2018.

Similar to other hydrodynamic models, GLM assumes some simplifications, such as the one-dimensional assumption inherent to the model configuration, which may introduce a level of uncertainty to the simulation results. Additionally, the scarcity of field data could impair the model's ability to reproduce the thermal behaviour accordingly. For instance, a regression-based statistical approach was adopted to provide daily inflow temperature as input to the model. Despite the existence of uncertainties in inflow temperature prediction, the model could meaningfully relate the hydro-meteorological forcing to the seasonal stratification dynamics in Barra Bonita Reservoir.

We are aware that the collection of longer and more detailed input data could help refine the simulated magnitudes of trends. Nonetheless, the uncertainties of model results are not expected to change the key conclusion of the existence of a significant warming trend, which was found along the water column in the Barra Bonita Reservoir for the 1993–2018 period. The detrended analysis corroborated those trends regardless of changes in wind speed, which may be considered the most uncertain forcing variable, which is a good indication of the warming in the reservoir.

Finally, the simulation comprised the complete period of available input data; a total of 26 years. This period is not long enough when studying temporal changes of environmental variables. Continuous field campaigns will be necessary to encompass the long-term variability of hydrodynamic processes.

4.2 Thermal response of a subtropical reservoir under climate change

A consistent annual temperature increase was detected along the water column revealing the process of Barra Bonita Reservoir warming up with positive trends from the surface (1.02 °C per decade) to the bottom (0.33 °C per decade). In subtropical lentic systems, increase water temperature may bring greater impacts on thermal stratification when compared to lakes and reservoirs in higher latitudes because the nonlinear relationship between water temperature and density is characterized by a stronger density response at higher temperatures. At around 24 °C, small temperature increases lead to relatively high stability increases (Lewis 1996). The warm surface in Barra Bonita Reservoir (mean temperature of 23.4 ± 3.6 °C) resulted in a density gradient strong enough to hold stratification during several days, increasing the number of stratified days at 19.4 days per decade, a rate greater than reported for lakes across the Northern hemisphere (4.13 days per decade, Woolway et al. 2019). This evidence corroborates that tropical water bodies tend to be more sensitive to climate change in terms of stability and resistance to mixing than lakes in temperate and arctic regions (Saulnier-Talbot et al. 2014; Kraemer et al. 2015).

The short hydraulic residence time of Barra Bonita Reservoir (0.28 years) may also contribute to the reservoir warming trending. The shorter the residence time, the greater the importance of the interaction between the reservoir and its tributaries on the hydrodynamic processes (Carmack et al. 1986). Although available data do not allow us to confirm it, the inflow water temperature has probably been experiencing some degree of warming up due to air temperature increase, which would intensify the warming trend in a such short residence time system.

In this study, results indicate that bottom waters are significantly warming, mainly during autumn and winter. Reported impacts of the warming climate on the temperature of deep waters reveal an inconsistent response among lentic systems, which were are either cooling (Magee and Wu 2017; Magee et al. 2016), showing no trends (Winslow et al. 2015), or in some cases, warming (Peeters et al. 2002). Conceptually, large and deep lakes experience increasing hypolimnic temperatures as they integrate the effects of meteorological forcing over longer periods of time, thus being able to carryover heat from one year to the next, while small and shallow lakes show only slight or no significant trends of rising hypolimnic temperatures due to the rapid loss of heat in autumn and winter (under ice-free condition) (Ficker et al. 2017). However, bottom waters may respond in more complex and variable ways (Butcher et al. 2015); thus, divergent patterns from the theoretical background may occur due to the fact that hypolimnion temperatures are generally disconnected from atmospheric forcing and may respond to different drivers of the thermal structure (Richardson et al. 2017). For instance, deep waters in Lake Malawi (East Africa) are warming at 0.1 °C per decade due to reduced cold-water intrusions in warmer winters (Vollmer et al. 2005); deep waters in twelve lakes across Europe are warming at a similar rate of 0.1–0.2 °C per decade due to the mesoscale signal from the North Atlantic Oscillation (Dokulil et al. 2006); and SAMO Lake (Mexico) is profoundly warming (1.136 °C per decade) at a rate about ten times larger than the mean global warming rate caused by thermal diffusion between surface and bottom water layers (Cardoso-Mohedano et al. 2019).

Barra Bonita Reservoir has a polymictic behaviour and surface waters are frequently mixed down to deeper layers efficiently transferring heat from the surface to bottom layers (Fig. S9).

According to model results, on average, water temperature at 10 m depth increases by 0.31 °C in the first day of a mixing event succeeding a stratification period. Furthermore, the amount of heat input into deep waters is further enhanced in this reservoir by the outlet structure and the high water level fluctuation, which are intrinsic characteristics of human-made and human-operated aquatic systems (Fig. S12). The outlet structure is a typical component of many reservoirs and may have a significant effect on the transfer and storage of heat in the water body primarily by determining the thermocline depth and hypolimnion volume (Casamitjana et al. 2003). In Barra Bonita Reservoir, water withdrawn occurs at 6.5 m from the bottom, which favours the storage of heat in the water body by retaining warmer surface water (23.4 °C on average) while withdrawing a volume with lower temperature (22.5 °C on average).

Additionally, reservoirs typically have more variable and complex hydrology than lakes due to anthropogenic operation of inflows and outflows, resulting in high water level fluctuations. In Barra Bonita Reservoir, the mean annual water level variation is about 5.0 m. The reservoir filling up occurs during summer and autumn (wet season) and its drawdown over winter and spring (dry season). When the reservoir is shallower, its thermal stability is reduced and less energy is required to mix the water column (Soares et al. 2019). Mixing during winter following lower air temperatures, a typical behaviour of subtropical lakes (Lewis 1996), is then amplified in subtropical reservoirs by the artificially imposed shallower depth in this season. Besides, as the reservoir's depth, surface area, and volume decrease with drawdown, the thermal inertia decreases in the shallower water body, ultimately reducing the time lag between air warming and water temperature variations (Toffolon et al. 2020).

4.3 Driving factors of trends in water temperature indicators

The significant trend in the observed air temperature, with an annual rate of 0.43 °C/decade, was in the range of those observed in different sites across the globe (Zhang et al. 2015; Schmid and Koster 2016; Winslow et al. 2017). In general, air temperature is believed to be the main driver of lake surface temperature changes (Huang et al. 2017) due to its influence on both sensible and latent heat exchange, and in the net longwave radiation. Overall, the highest increase in water temperature from the surface to the bottom during winter (Fig 3) is consistent with and likely related to the higher air warming trend rate in this season (Fig. 5). Increase trends in deepwater temperatures at Barra Bonita Reservoir are directly coupled to the increase in the air temperature. The peak in the increasing rate of air temperature in June followed by a peak in the warming rate of water temperature in July exhibits how bottom layer temperatures are closely related to the near-surface temperature in this reservoir.

The significant warming of water temperature consistently exceeded the air temperature trends on annual and monthly scales, which may be explained by changes in other forcing variables influencing water warming. In the present study, the mechanism explaining a water warming trend stronger than the air temperature trend is an abrupt change in the wind speed time series. Wind speed acts both on the exchange of latent and sensible heat and also forces the motion of water and thereby turbulent transport.

The lower wind speed was the main driver of the change in the thermal conditions of the Barra Bonita Reservoir by enhancing the duration of stratification events from 2009. The detrended simulation generated an artificial condition by removing the natural variability in wind speed, resulting in a permanently mixed water column. This analysis revealed that the annual trends in air temperature, air relative humidity, and rainfall, although significant, were not enough to promote such hydrodynamic change. Therefore, air temperature and wind speed were the main driving factors of the warming trends in the reservoir. Each driver alone may not be strong enough to cause a major shift in the temperature indicators, but their combined effects interact synergistically by increasing gains (increasing air temperature) and decreasing losses (decreasing wind speed) from the energy budget.

Increased air temperature and decreased wind speed were also drivers of warmer temperatures and stronger stability in other lentic systems (Zhang et al. 2015; Magee and Wu 2017; Moras et al. 2019; Woolway et al. 2019). The relative contribution of each forcing variable merits further investigation, but it is beyond the scope of the present study. Not only long-term temporal changes over the study period but also antecedent conditions, large-scale meteorological forcing, and anomalies in atmospheric circulation may also be important drivers of water warming (Zhong et al. 2016).

4.4 Potential implications on water quality

Understanding water temperature trends and changes in the thermal structure of reservoirs is of great ecological significance because they can trigger chemical reactions, cellular temperature-dependent processes, and impact the habitat for macroinvertebrates and fishes, exerting a strong control on the ecosystem's biogeochemistry and ecology. Climate change will not result in a single change, but rather in a set of related consequences, and may pose further threats and complexity to freshwater ecosystems functioning (Sahoo et al. 2016) potentially impairing current multiple uses of water and its ecosystem services.

Warming trends and stronger stability suggest that the current eutrophication-related problems will probably become more drastic, adding further stress to the ecosystem, hampering the path to its sustainable use. One can foresee that mixing events could be severely reduced by the stronger stability if detected trends continue in the future. Greater water column stability and warmer temperatures, especially during winter, may favour algal blooms (Elliott 2012) and extend its occurrence beyond summer season, as typically occurs, with further implications to the general reservoir ecology. Moreover, higher temperatures may exceed limits not only for the phytoplankton, but also for fishes, allowing some species to expand their range and forcing others to decline (Bachmann et al. 2020). In the tropics, the water temperature increase may strongly threaten species currently exposed to high temperatures, as the thermal optima and limits are close to current maximum ambient temperatures, leaving them with little scope for adapting to higher temperatures (Harrod 2015).

The present results can be used as a proxy for future planning. Deeper insights could come from a robust and integrated climate–hydrologic–reservoir–ecological modelling framework (Sharma et al. 2018), moving towards a more resilient society and ecosystem to the reservoir warming up. While not in the scope of this study, management techniques at reservoir and catchment scales have the potential to buffer climate change signals (Yasarer and Sturm 2016).

5 Conclusions

A simulation of hydrodynamics in the Barra Bonita Reservoir from 1993 to 2018 was conducted by applying a one-dimensional hydrodynamic model calibrated and validated using field data from the study site. The mass balance and the vertical water temperature were reliably reproduced, revealing that the warming up process in the reservoir is already underway. A significant increasing temperature trend was detected along the whole water column, with annual trends varying from 0.33 °C/decade at the bottom to 1.02 °C/decade at the surface; stronger stability at a rate of 12.83 J m^{-2} per decade; and an increase of 19.40 stratified days per decade.

Surface water temperature in Barra Bonita Reservoir and the number of stratification events are increasing as a response to increase air temperature and decrease wind speed. Such changes in meteorological forcing also impact the temperature of deep waters because frequent mixing events transfer heat from the surface to the bottom, mainly during the dry and cold season when water level is lower and colder water is withdrawn from a deep outlet structure. Furthermore, the greatest rates of air temperature increase were detected during the dry cold season and directly reflected in the deepwater warming in the reservoir.

Even though many studies have evaluated the impacts of climate change on lentic systems under temperate climate, the literature is consensual that limited information is available for water bodies in lower latitudes. The present study identifies hydrodynamic changes in Barra Bonita Reservoir related to changes in meteorological forcing and discusses how the interaction between this latter and climatic, hydrological, hydrodynamic, and operation characteristics reflects on the reservoir thermal response. The present findings are extendable to other polymictic reservoirs in the tropics and bring a new contribution to understand how such water bodies may respond to climate changes.

Water temperature is a key variable controlling a large variety of physical, ecological, and biogeochemical processes; thus, the current results might be of primary interest to water managers, as water warming will likely impact the associated ecosystems by the exacerbation of existing water quality problems. Expecting that climate is becoming more variable, resources need to be targeted at devising long-term monitoring programs and integrated modelling frameworks towards achieving a more accurate understanding of climate change effects on water resources that may help guide adaptation strategies.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10584-021-03124-x.

Acknowledgements The authors are grateful to the National Institute of Meteorology (INMET), the National Water Agency (ANA), and the Environmental Company of the State of São Paulo (CETESB) for the available data.

Funding This work was supported by the National Council for Scientific and Technological Development (CNPq).

References

Adrian R, O'Reilly CM, Zagarese H et al (2009) Lakes as sentinels of climate change. Limnol Oceanogr 54: 2283–2297. https://doi.org/10.4319/lo.2009.54.6_part_2.2283

ANA (2018a) Report on dam safety 2017. Brasília

ANA (2018b) Reservoirs' Monitoring System [Sistema de Acompanhamento de Reservatórios]. In: Agência Nac. Águas. https://www.ana.gov.br/sar/ Accessed 03 September 2020

ANA (2019) Hidroweb. http://wwwsnirhgovbr/hidroweb Accessed 03 September 2020

Angstrom A (1924) Solar and atmospheric radiation. Q J R Meteorol Soc 50:121–126

Bachmann RW, Canfield DE, Sharma S, Lecours V (2020) Warming of near-surface summer water temperatures in lakes of the conterminous United States. Water (Switzerland) 12. https://doi.org/10.3390/w12123381

Bayer TK, Burns CW, Schallenberg M (2013) Application of a numerical model to predict impacts of climate change on water temperatures in two deep, oligotrophic lakes in New Zealand. Hydrobiologia 713:53–71. https://doi.org/10.1007/s10750-013-1492-y

Bennett ND, Croke BFW, Guariso G et al (2013) Characterising performance of environmental models. Environ Model Softw 40:1–20. https://doi.org/10.1016/j.envsoft.2012.09.011
Bruce LC, Frassl MA, Arhonditsis GB et al (2018) A multi-lake comparative analysis of the General Lake Model (GLM): stress-testing across a global observatory network. Environ Model Softw 102:274–291. https://doi.org/10.1016/j.envsoft.2017.11.016
Bueche T, Hamilton DP, Vetter M (2017) Using the General Lake model (GLM) to simulate water temperatures and ice cover of a medium-sized Lake: a case study of Lake Ammersee, Germany. Environ Earth Sci 76:461. https://doi.org/10.1007/s12665-017-6790-7
Bueche T, Wenk M, Poschlod B et al (2019) glmGUI v1.0: an R-based Geographical User Interface and toolbox for GLM (General Lake Model) simulations. Geosci Model Dev Discuss:1–41. https://doi.org/10.5194/gmd-2018-314
Butcher JB, Nover D, Johnson TE, Clark CM (2015) Sensitivity of lake thermal and mixing dynamics to climate change. Clim Chang 129:295–305. https://doi.org/10.1007/s10584-015-1326-1
Cardoso-Mohedano JG, Sanchez-Cabeza JA, Ruiz-Fernández AC et al (2019) Fast deep water warming of a subtropical crater lake. Sci Total Environ 691:1353–1361. https://doi.org/10.1016/j.scitotenv.2019.07.183
Carmack EC, Wiegand RC, Daley RJ et al (1986) Mechanisms influencing the circulation and distribution of water mass in a medium residence-time lake. Limnol Oceanogr 31:249–265. https://doi.org/10.4319/lo.1986.31.2.0249
Casamitjana X, Serra T, Colomer J et al (2003) Effects of the water withdrawal in the stratification patterns of a reservoir. Hydrobiologia 504:21–28. https://doi.org/10.1023/B:HYDR.0000008504.61773.77
CETESB (2019) Publications and Reports [Publicações e Relatórios]. In: Cia. Ambient. do Estado São Paulo. https://cetesb.sp.gov.br/aguas-interiores/publicacoes-e-relatorios/ Accessed 03 September 2020
Corrêa Filho CRR, Albertin LL, Mauad FF (2003) Determination of quota x area x volume using the Acoustic Doppler Profiler (ADP) in Barra Bonita Reservoir - SP [Determinação dos Polinômios Cota X Área X Volume Utilizando a Sonda Acoustic Doppler Profiler (ADP) no Reservatório de Barra Bonita – SP]. Minerva 2:79–90
Dokulil MT, Jagsch A, George GD et al (2006) Twenty years of spatially coherent deepwater warming in lakes across Europe related to the North Atlantic Oscillation. Limnol Oceanogr 51:2787–2793. https://doi.org/10.4319/lo.2006.51.6.2787
Elliott JA (2012) Is the future blue-green? A review of the current model predictions of how climate change could affect pelagic freshwater cyanobacteria. Water Res 46:1364–1371. https://doi.org/10.1016/j.watres.2011.12.018
Fadel A, Lemaire BJ, Vinçon-Leite B et al (2017) On the successful use of a simplified model to simulate the succession of toxic cyanobacteria in a hypereutrophic reservoir with a highly fluctuating water level. Environ Sci Pollut Res 24:20934–20948. https://doi.org/10.1007/s11356-017-9723-9
Fenocchi A, Rogora M, Sibilla S, Dresti C (2017) Relevance of inflows on the thermodynamic structure and on the modeling of a deep subalpine lake (Lake Maggiore, Northern Italy/Southern Switzerland). Limnologica 63:42–56. https://doi.org/10.1016/j.limno.2017.01.006
Ficker H, Luger M, Gassner H (2017) From dimictic to monomictic: empirical evidence of thermal regime transitions in three deep alpine lakes in Austria induced by climate change. Freshw Biol 62:1335–1345. https://doi.org/10.1111/fwb.12946
Hamilton DP, Schladow SG (1997) Prediction of water quality in lakes and reservoirs. Part I - model description. Ecol Model 96:91–110. https://doi.org/10.1016/S0304-3800(96)00062-2
Hammer Ø (2019) Manual Past 3.25. Ref. Man. 275
Harrod C (2015) Climate change and freshwater fisheries. Freshwater Fisheries Ecology, pp 641–694
Hayes NM, Deemer BR, Corman JR et al (2017) Key differences between lakes and reservoirs modify climate signals: a case for a new conceptual model. Limnol Oceanogr Lett 2:47–62. https://doi.org/10.1002/lol2.10036
He W, Lian J, Zhang J et al (2019) Impact of intra-annual runoff uniformity and global warming on the thermal regime of a large reservoir. Sci Total Environ 658:1085–1097. https://doi.org/10.1016/j.scitotenv.2018.12.207
Hipsey MR, Bruce LC, Hamilton DP (2014) General lake model - model overview and user information
Hipsey MR, Bruce LC, Boon C et al (2019) A General Lake model (GLM 3.0) for linking with high-frequency sensor data from the Global Lake Ecological Observatory Network (GLEON). Geosci Model Dev 12:473–523. https://doi.org/10.5194/gmd-12-473-2019
Hirsch RM, Slack JR, Smith RA (1982) Techniques of trend analysis for monthly water quality data. Water Resour Res 18:107–121. https://doi.org/10.1029/WR018i001p00107
Hornung R (2002) Numerical modelling of stratification in Lake Constance with the 1-D hydrodynamic model DYRESM

Huang L, Wang J, Zhu L et al (2017) The warming of large lakes on the Tibetan Plateau: evidence from a lake model simulation of Nam Co, China, during 1979–2012. J Geophys Res Atmos 122:95–107. https://doi.org/10.1002/2017JD027379
IBGE (2018) Monitoring of land cover and use. In: Brazilian Inst. Geogr. Stat. https://www.ibge.gov.br/geociencias/informacoes-ambientais/cobertura-e-uso-da-terra Accessed 03 September 2020
Idso SB (1973) On the concept of lake stability. Limnol Oceanogr 18:681–683
Imberger J, Patterson JC (1990) Physical limnology. In: Hutchinson JW, Wu TY (eds) Advances in Applied Mechanics. Academic Press Inc., pp 303–476
INMET (2019) Brazilian Climatological Normals 1981-2010 [Normais climatológicas do Brasil 1981-2010]. In: Inst. Nac. Meteorol. http://www.inmet.gov.br Accessed 03 September 2020
INMET (2020) Automatic monitoring stations [Estações de Monitoramento Automático]. In: Inst. Nac. Meteorol. http://www.inmet.gov.br/portal/index.php?r=estacoes/estacoesAutomaticas Accessed 03 September 2020
Janssen ABG, Hilt S, Kosten S et al (2020) Shifting states, shifting services: linking regime shifts to changes in ecosystem services of shallow lakes. Freshw Biol. https://doi.org/10.1111/fwb.13582
Kerimoglu O, Rinke K (2013) Stratification dynamics in a shallow reservoir under different hydro-meteorological scenarios and operational strategies. Water Resour Res 49:7518–7527. https://doi.org/10.1002/2013WR013520
Kraemer BM, Anneville O, Chandra S et al (2015) Morphometry and average temperature affect lake stratification responses to climate change. Geophys Res Lett 42:4981–4988. https://doi.org/10.1002/2015GL064097
Lehner B, Liermann CR, Revenga C et al (2011) High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. Front Ecol Environ 9:494–502. https://doi.org/10.1890/100125
Lewis WM (1996) Tropical lakes: how latitude makes a difference. Perspect Trop Limnol 43–64
Lewis WM (2000) Basis for the protection and management of tropical lakes. Lakes Reserv Res Manag 5:35–48. https://doi.org/10.1046/j.1440-1770.2000.00091.x
Lewis WM Jr, McCutchan JH Jr, Roberson J (2019) Effects of climatic change on temperature and thermal structure of a mountain reservoir. Water Resour Res 55:1988–1999. https://doi.org/10.1029/2018WR023555
Magee MR, Wu CH (2017) Response of water temperatures and stratification to changing climate in three lakes with different morphometry. Hydrol Earth Syst Sci 21:6253–6274. https://doi.org/10.5194/hess-21-6253-2017
Magee MR, Wu CH, Robertson DM et al (2016) Trends and abrupt changes in 104-years of ice cover and water temperature in a dimictic lake in response to air temperature, wind speed, and water clarity drivers. Hydrol Earth Syst Sci Discuss 20:1681–1702. https://doi.org/10.5194/hess-20-1681-2016
Mi C, Sadeghian A, Lindenschmidt KE, Rinke K (2019) Variable withdrawal elevations as a management tool to counter the effects of climate warming in Germany's largest drinking water reservoir. Environ Sci Eur 31. https://doi.org/10.1186/s12302-019-0202-4
Moras S, Ayala AI, Pierson DC (2019) Historical modelling of changes in Lake Erken thermal conditions. Hydrol Earth Syst Sci 23:5001–5016. https://doi.org/10.5194/hess-23-5001-2019
O' Reilly CM, Sharma S, Gray DK et al (2015) Rapid and highly variable warming of lake surface waters around the globe. Geophys Res Lett 42:773–781. https://doi.org/10.1002/2015GL066235
Peeters F, Livingstone DM, Goudsmit GH et al (2002) Modeling 50 years of historical temperature profiles in a large central European lake. Limnol Oceanogr 47:186–197. https://doi.org/10.4319/lo.2002.47.1.0186
Poole HH, Atkins WRG (1929) Photo-electric measurements of submarine illumination throughout the year. J Mar Biol Assoc United Kingdom 16:297–324
Prescott JA (1940) Evaporation from a water surface in relation to solar radiation. Trans R Soc South Aust 64:114–118
Ramírez A, Caballero M, Vázquez G, Colón-Gaud C (2020) Preface: recent advances in tropical lake research. Hydrobiologia 847:4143–4144. https://doi.org/10.1007/s10750-020-04443-3
Read JS, Hamilton DP, Jones ID et al (2011) Derivation of lake mixing and stratification indices from high-resolution lake buoy data. Environ Model Softw 26:1325–1336. https://doi.org/10.1016/j.envsoft.2011.05.006
Read JS, Winslow LA, Hansen GJA et al (2014) Simulating 2368 temperate lakes reveals weak coherence in stratification phenology. Ecol Model 291:142–150. https://doi.org/10.1016/j.ecolmodel.2014.07.029
Richardson DC, Melles SJ, Pilla RM et al (2017) Transparency, geomorphology and mixing regime explain variability in trends in lake temperature and stratification across Northeastern North America (1975-2014). Water (Switzerland) 9. https://doi.org/10.3390/w9060442
Rolighed J, Jeppesen E, Søndergaard M et al (2016) Climate change will make recovery from eutrophication more difficult in shallow Danish Lake Søbygaard. Water (Switzerland) 8:1–20. https://doi.org/10.3390/w8100459

Sahoo GB, Forrest AL, Schladow SG et al (2016) Climate change impacts on lake thermal dynamics and ecosystem vulnerabilities. Limnol Oceanogr 61:496–507. https://doi.org/10.1002/lno.10228
Salmi T, Maatta A, Anttila P, et al (2002) Detecting trends of annual values of atmospheric pollutants by the Mann-Kendall test and Sen's slope estimates - the Excel template application MAKESENS 35
Saulnier-Talbot É, Gregory-Eaves I, Simpson KG et al (2014) Small changes in climate can profoundly alter the dynamics and ecosystem services of tropical crater lakes. PLoS One 9:1–8. https://doi.org/10.1371/journal.pone.0086561
Schmid M, Koster O (2016) Excess warming of a Central European lake driven by solar brightening. Water Resour Res 52:8103–8116. https://doi.org/10.1002/2016WR018651
Sen PK (1968) Estimated of the regression coefficient based on Kendall's Tau. J Am Stat Assoc 63:1379–1389
Sharma A, Hamlet AF, Fernando HJS et al (2018) The need for an integrated land-lake-atmosphere modeling system, exemplified by North America's Great Lakes Region. Earth's Futur 6:1366–1379. https://doi.org/10.1029/2018EF000870
Silva TFG, Vinçon-Leite B, Lemaire BJ et al (2019) Impact of urban stormwater runoff on cyanobacteria dynamics in a tropical urban lake. Water 11. https://doi.org/10.3390/w11050946
Snortheim CA, Hanson PC, McMahon KD et al (2017) Meteorological drivers of hypolimnetic anoxia in a eutrophic, north temperate lake. Ecol Model 343:39–53. https://doi.org/10.1016/j.ecolmodel.2016.10.014
Soares LMV, Silva, TF das G, Vinçon-Leite B, et al. (2019) Modelling drought impacts on the hydrodynamics of a tropical water supply reservoir. Inl Waters 9:422–437. https://doi.org/10.1080/20442041.2019.1596015
Soares LMV, Calijuri M do C, Silva, TF das G, et al. (2020) A parameterization strategy for hydrodynamic modelling of a cascade of poorly monitored reservoirs in Brazil. Environ Model Softw 134:. https://doi.org/10.1016/j.envsoft.2020.104803
Tanentzap AJ, Hamilton DP, Yan ND (2007) Calibrating the Dynamic Reservoir Simulation Model (DYRESM) and filling required data gaps for one-dimensional thermal profile predictions in a boreal lake. Limnol Oceanogr Methods 5:484–494. https://doi.org/10.4319/lom.2007.5.484
Tiba C (2000) Solarimetric atlas of Brazil: terrestrial database [atlas Solarimétrico do Brasil: banco de dados Terrestres]. Recife, 111 p
Toffolon M, Piccolroaz S, Calamita E (2020) On the use of averaged indicators to assess lakes' thermal response to changes in climatic conditions. Environ Res Lett 15. https://doi.org/10.1088/1748-9326/ab763e
Vinçon-Leite B, Lemaire BJ, Khac VT, Tassin B (2014) Long-term temperature evolution in a deep sub-alpine lake, Lake Bourget, France: how a one-dimensional model improves its trend assessment. Hydrobiologia 731:49–64. https://doi.org/10.1007/s10750-014-1818-4
Vollmer MK, Bootsma HA, Hecky RE et al (2005) Deep-water warming trend in Lake Malawi, East Africa. Limnol Oceanogr 50:727–732. https://doi.org/10.4319/lo.2005.50.2.0727
Weber M, Rinke K, Hipsey MR, Boehrer B (2017) Optimizing withdrawal from drinking water reservoirs to reduce downstream temperature pollution and reservoir hypoxia. J Environ Manag 197:96–105. https://doi.org/10.1016/j.jenvman.2017.03.020
Weinberger S, Vetter M (2012) Using the hydrodynamic model DYRESM based on results of a regional climate model to estimate water temperature changes at Lake Ammersee. Ecol Model 244:38–48. https://doi.org/10.1016/j.ecolmodel.2012.06.016
Williamson CE, Saros JE, Vincent WF, Smol JP (2009) Lakes and reservoirs as sentinels, integrators, and regulators of climate change. Limnol Oceanogr 54:2273–2282. https://doi.org/10.4319/lo.2009.54.6_part_2.2273
Willmott CJ (1981) On the validation of models. Phys Geogr 2:184–194. https://doi.org/10.1080/02723646.1981.10642213
Winslow LA, Read JS, Hansen GJA, Hanson PC (2015) Small lakes show muted climate change signal in deepwater temperatures. Geophys Res Lett 42:355–361. https://doi.org/10.1002/2014GL062325
Winslow LA, Read JS, Hansen GJA et al (2017) Seasonality of change: summer warming rates do not fully represent effects of climate change on lake temperatures. Limnol Oceanogr 62:2168–2178. https://doi.org/10.1002/lno.10557
Woolway RI, Merchant CJ (2019) Worldwide alteration of lake mixing regimes in response to climate change. Nat Geosci 12:271–276. https://doi.org/10.1038/s41561-019-0322-x
Woolway RI, Merchant CJ, Van Den Hoek J et al (2019) Northern hemisphere atmospheric stilling accelerates Lake thermal responses to a warming world. Geophys Res Lett 46:11983–11992. https://doi.org/10.1029/2019GL082752
Yasarer LMW, Sturm BSM (2016) Potential impacts of climate change on reservoir services and management approaches. Lake Reserv Manag 32:13–26. https://doi.org/10.1080/10402381.2015.1107665
Zarfl C, Lumsdon AE, Berlekamp J et al (2014) A global boom in hydropower dam construction. Aquat Sci 77:161–170. https://doi.org/10.1007/s00027-014-0377-0

Zhang Y, Wu Z, Liu M et al (2015) Dissolved oxygen stratification and response to thermal structure and long-term climate change in a large and deep subtropical reservoir (Lake Qiandaohu, China). Water Res 75:249–258. https://doi.org/10.1016/j.watres.2015.02.052
Zhong Y, Notaro M, Vavrus SJ, Foster MJ (2016) Recent accelerated warming of the Laurentian Great Lakes: physical drivers. Limnol Oceanogr 61:1762–1786. https://doi.org/10.1002/lno.10331

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Affiliations

Laura Melo Vieira Soares[1] • Maria do Carmo Calijuri[1] • Talita Fernanda das Graças Silva[2] • Evlyn Marcia Leão de Moraes Novo[3]

Maria do Carmo Calijuri
calijuri@sc.usp.br

Talita Fernanda das Graças Silva
talita.silva@ehr.ufmg.br

Evlyn Marcia Leão de Moraes Novo
evlyn.novo@inpe.br

[1] Department of Hydraulics and Sanitation, University of São Paulo at São Carlos School of Engineering, Av. Trabalhador São Carlense 400, São Carlos, SP 13566-590, Brazil

[2] Department of Hydraulic Engineering and Water Resources, Universidade Federal de Minas Gerais, Av. Presidente Antônio Carlos 6627, Belo Horizonte, MG 31270-901, Brazil

[3] Remote Sensing Division, National Institute of Space Research (INPE), Av. dos Astronautas 1758, São José dos Campos, SP 12227-010, Brazil