



# Chlorophyll-a prediction in tropical reservoirs as a function of hydroclimatic variability and water quality

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## Abstract

The study goal was to determine spatiotemporal variations in chlorophyll-a (Chl-a) concentration using models that combine hydroclimatic and nutrient variables in 150 tropical reservoirs in Brazil. The investigation of seasonal variability indicated that Chl-a varied in response to changes in total nitrogen (TN), total phosphorus (TP), volume (V), and daily precipitation (P). Therefore, an empirical model for Chl-a prediction based on the product of TN, TP, and normalized functions of V and P was proposed, but their individual exponents as well as a general multiplicative factor were adjusted by linear regression for each reservoir. The fitted relationships were capable of representing algal temporal dynamics and blooms, with an average coefficient of determination of  $R^2=0.70$ . The results revealed that nutrients yielded better predictability of Chl-a than hydroclimatic variables. Chl-a blooms presented seasonal and interannual variability, being more frequent in periods of high precipitation and low volume. The equations demonstrate different Chl-a responses to the parameters. In general, Chl-a was positively related to TN and/or TP. However, in some cases (22%), high nutrient concentrations reduced Chl-a, which was attributed to limited phytoplankton growth driven by light deficiency due to increased turbidity. In 49% of the models, precipitation intensified Chl-a levels, which was related to increases in the nutrient concentration from external sources in rural watersheds. Contrastingly, 51% of the reservoirs faced a decrease in Chl-a with precipitation, which can be explained by the opposite effect of dilution of nutrient concentration at the reservoir inlet in urban watersheds. In terms of volume, in 67% of the reservoirs, water level reduction promoted an increase in Chl-a as a response to higher nutrient concentration. In the other cases, Chl-a decreased with lower water levels due to wind-induced destratification of the water column, which potentially decreased the internal nutrient release from bottom sediment. Finally, applying the model to the two largest studied reservoirs showed greater sensitivity of Chl-a to changes in water use classes regarding variations in TN, followed by TP, V, and P.

**Keywords** Algal blooms · Eutrophication · Hydrology · Limnology · Water quality modeling

## Introduction

Eutrophication is one of the world's most critical environmental issues concerning reservoirs and other aquatic environments. Excessive nutrient loading into water bodies is considered the main induction factor of water eutrophication (Paerl et al. 2016; Andrade et al. 2020), particularly total nitrogen (TN) and total phosphorus (TP), as they are

essential for the growth of phytoplankton (microalgae and cyanobacteria) and macrophytes (aquatic plants) (Schindler 2006; McCrackin et al. 2017). However, although often associated with consistent nutrient enrichment, the mechanisms that dictate eutrophication's effects on uncontrolled phytoplankton growth and algae blooms are not yet fully understood (Padedda et al. 2017; Namsaraev et al. 2020). In recent years, outbreaking of harmful algal blooms is becoming more frequent, posing severe risks not only to water quality but also to human health and economic development (Jargal et al. 2021; Li et al. 2021a, b). Therefore, in regions with high climate variability and frequent occurrence of extreme droughts and reflooding events, such as the Brazilian Northeast, reservoirs are particularly susceptible to water quality deterioration and subsequent eutrophication due to continued anthropogenic pressure on water bodies

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(Pontes Filho et al. 2020; Wiegand et al. 2021; Carvalho et al. 2022).

Chlorophyll-a concentration (Chl-a) has been a useful indicator for measuring phytoplankton or algal biomass (Li et al. 2021a, b). For this reason, exploring the complex relationships between the aquatic environment and Chl-a behavior has always been a crucial strategy for sustainability and better management of water resources (Lu et al. 2016; Luo et al. 2019). Initially, mathematical models were developed by Vollenweider (1968), Dillon and Rigler (1974), Jones and Bachmann (1976), and Pridmore et al. (1985), relating Chl-a in lakes and marine environments to phosphorus or nitrogen through linear or non-linear regressions. More recently, researchers have used empirically based models to explore the correlation of Chl-a with other parameters such as reservoir characteristics, watershed occupation, and physicochemical characteristics of the water (Tang et al. 2019; Franklin et al. 2020; Hara et al. 2020; Yuan and Jones 2020; Mamun et al. 2021a) and hydroclimatic variations (volume, precipitation, temperature, and wind speed) (Wang et al. 2014; Paerl et al. 2016; Tang et al. 2019). Despite being simple to implement, these models are developed for lakes and reservoirs with regional characteristics, which can lead to significant prediction errors in regions with water deficits and a high degree of uncertainty in the spatio-temporal distribution of rainfall, such as tropical reservoirs (Chaves et al. 2019; Andrade et al. 2020; Lopes et al. 2021).

With the development of artificial intelligence, other models and approaches have been used to understand primary production in aquatic environments, such as machine learning models (Lu et al. 2016; Franklin et al. 2020; Franklin et al. 2020; Liao et al. 2021; Thi Hoang Yen et al. 2021; Carvalho et al. 2022; Chusnah and Chu 2022; Kim and Ahn 2022) and monitoring through remote sensing satellites (Gidudu et al. 2021; Mamun et al. 2021a, b; Rotta et al. 2021; Stefanidis et al. 2021; Aranha et al. 2022; Kayastha et al. 2022). Despite predicting Chl-a levels with satisfactory accuracy, these models strongly depend on a large number of input variables (extensive time series, initial conditions and boundary conditions), which limits their application in regions with data scarcity (Park et al. 2015; Zeng et al. 2017). Although several models in the literature attempt to predict the Chl-a's concentration and blooms in aquatic environments, due to the complexity and nonlinearity associated with the factors involved, few research focused on the development of simple empirical models that combine hydroclimatic and nutrient factors in tropical reservoirs, particularly in the northeast region of Brazil.

This study proposes models that innovatively combine hydroclimatic and nutrient variables to predict Chl-a levels and blooms through simple empirical equations in 150 tropical reservoirs located in the state of Ceará, in the Brazilian Northeast. In this water-scarce region with relatively high

population density (approximately 9 million inhabitants within an area of 149,000 km<sup>2</sup>), the construction of reservoirs to store water during wet periods has been the solution to cope with water shortage and recurrent droughts, resulting in watersheds with dense reservoir networks subject to significant variations in precipitation and volume, high trophic levels, and recurrent cyanobacterial blooms (Rabelo et al. 2021; Rocha and Lima Neto 2021a; Wiegand et al. 2021; Lima Neto et al. 2022). Therefore, suitable models are required to predict Chl-a concentrations accurately. This study aims (1) to characterize the spatio-temporal variability of hydroclimatic and water quality parameters of the study reservoirs; (2) to identify the relevance of each input variable in the Chl-a dynamics; (3) to define the variables that best describe the concentration peaks; and (4) to simulate scenarios of water quality change using the empirical models developed for Chl-a prediction.

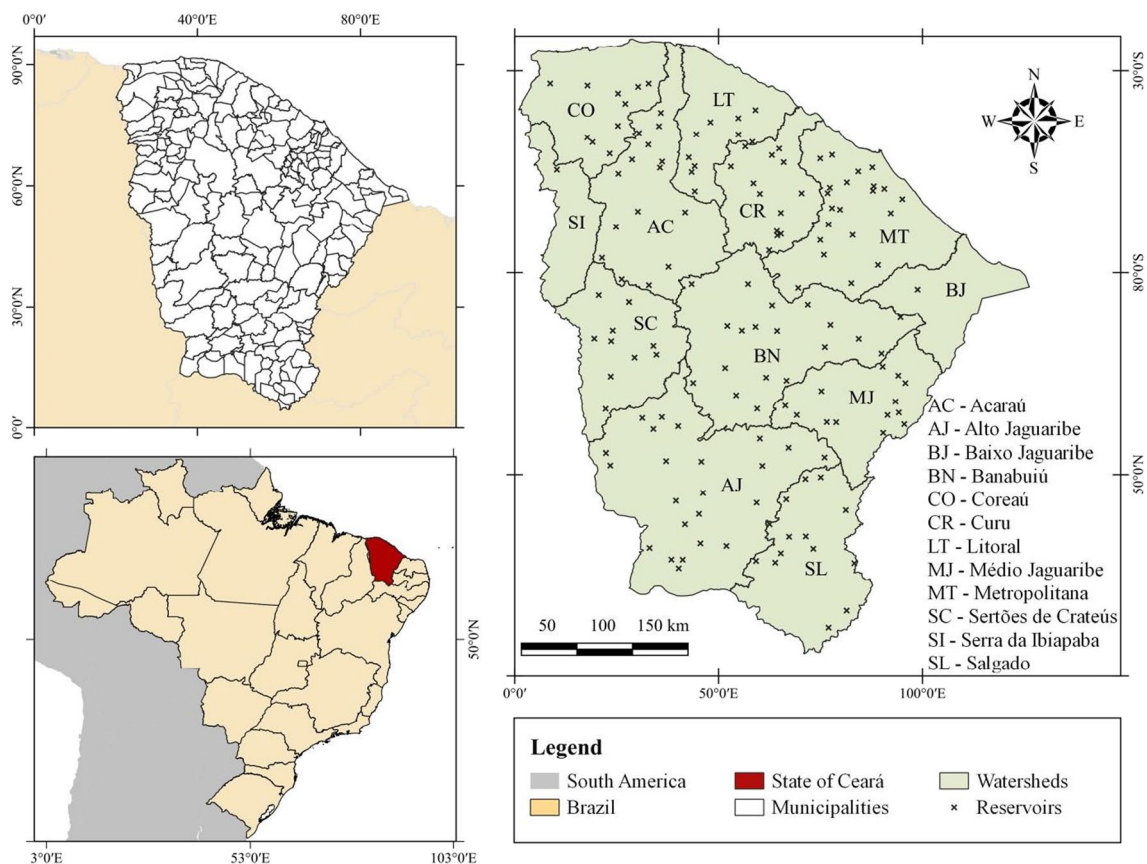
## Methodology

### Study sites and data collection

The study focused on 150 reservoirs in the State of Ceará, a tropical region of the Brazilian Northeast (Fig. 1). This region is characterized by a variable and irregular spatio-temporal distribution of precipitation, high evaporation rates, high stable temperatures (seasonal), and recurrent droughts (Carneiro et al. 2014; Rocha and Lima Neto 2021a). In this region, the average precipitation rates range from 550 to 1100 mm/year, and the rainy season comprises the period from January to May when about 80% of the annual precipitation occurs.

The analyzed data consists of 3835 sets of samples of nutrient concentrations (TN and TP), Chl-a concentrations, volumetric percentage (V), and daily precipitation (P) for 150 reservoirs distributed in the 12 hydrographic regions of the state of Ceará. The main water uses from these reservoirs are: human supply, aquaculture, fish farming, and irrigation. Artisanal fishing and family farming occur in 55% and 56% of these reservoirs, respectively. Therefore, the main non-point pollution sources are attributed to livestock, agriculture, soils, and point sources resulting from sewage and fish farming (Ceará 2018). Reservoirs with relevant aquaculture practices receive the most attention in mitigating the potential impacts of changes in water volume and quality, mainly due to economic losses related to these processes (Rocha and Lima Neto 2021a, b, 2022). The geographic location and storage capacity of the analyzed reservoirs are detailed in Table S1 in the supplementary material.

This research used data from publicly available databases. The historical series (2008–2021) of volumetric percentage and water quality parameters (TN, TP, and



**Fig. 1** Map of the study area geographic location (Ceará state, Brazil) showing sampling collection sites at each analyzed reservoir made available by the Ceará Water Resources Management Company (COGERH)

Chl-a) were obtained from the Ceará Hydrological Platform (Ceará 2021). The dataset of hydrological parameters and water quality of reservoirs made available by this platform results from a partnership between the Ceará State Water Resources Management Company (COGERH) and the Ceará State Water Resources Department (SRH). Monitoring is carried out in quarterly campaigns. Water quality information is obtained in the field through a multiparameter probe and water samples collected 0.3 m from the surface for laboratory analysis according to APHA (2005). The daily precipitation dataset was obtained from the Meteorology and Water Resources Foundation of Ceará (FUNCEME) (Ceará 2022a). Measurement stations in each reservoir or municipality in which they are located were selected according to data availability. The daily precipitation values were normalized through the relationship between the observed precipitation and the maximum precipitation identified in the series of each reservoir.

### Spatio-temporal analysis of parameters

Data were divided into three periods with similar intervals: P1 (2008–2012) ( $n = 504$ ), P2 (2013–2017) ( $n = 1646$ ), and

P3 (2018–2021) ( $n = 1685$ ). P2 represents a long and severe period of drought faced in the state of Ceará, triggered in 2012 (Araújo and Bronstert 2016; Wiegand et al. 2021). Each period's means, standard deviation, and maximum and minimum values were calculated for each basin. The mean concentrations of each basin were classified according to the class intervals presented in Table 1, which were defined based on the reference values suggested by CONAMA 357 (Brasil 2005). The variation of TN, TP, Chl-a, V, and P among the studied periods was statistically analyzed with the non-parametric Kruskal–Wallis test ( $p < 0.05$ ), since the observations have an unequal duration within each period.

### Empirical equations

In this study, to estimate the concentration of Chl-a in the reservoirs, an empirical model based on four components (TN, TP, V, and P) was developed. In order to include the contributions of each input in Chl-a concentration, Microsoft Excel® Solver add-in was used to define the exponents of the input variables in Eq. 1. Through the GRG (Generalized Reduced Gradient) solution method for linear and non-linear optimizations, the tool performs a

**Table 1** Classification intervals adopted for Chl-a, TN, and TP based on the water quality class suggested by CONAMA Resolution 357 for different uses of lentic water bodies. V represents the percent volume

Class	Chl-a ( $\mu\text{g.L}^{-1}$ )	TN ( $\text{mg.L}^{-1}$ )	TP ( $\text{mg.L}^{-1}$ )	V (%)	P (mm)
C1	$0 < \text{Chl-a} \leq 10$	$0.00 < \text{TN} \leq 1.00$	$0.00 < \text{TP} \leq 0.02$	$75 < V \leq 100$	$0.00 < P \leq 1.86$
C2	$10 < \text{Chl-a} \leq 30$	$1.00 < \text{TN} \leq 2.00$	$0.02 < \text{TP} \leq 0.03$	$50 < V \leq 75$	$1.86 < P \leq 3.74$
C3	$30 < \text{Chl-a} \leq 60$	$2.00 < \text{TN} \leq 5.60$	$0.03 < \text{TP} \leq 0.05$	$25 < V \leq 50$	$3.74 < P \leq 5.62$
C4	$\text{Chl-a} > 60$	$\text{TN} > 5.60$	$\text{TP} > 0.05$	$0 < V \leq 25$	$5.62 < P \leq 7.50$

of the reservoirs based on their total capacity. P(mm) is the average daily precipitation. Precipitation (P) limits were defined based on the minimum and maximum values observed in the sample

series of interactions in which a given set of cells (exponents a, b, c, d, and the multiplicative factor n) are changed to achieve the minimization of the chosen performance metric (RMSE) so that different coefficient values are estimated for each reservoir in the data set.

$$\text{Chl}_{a_{ij}} = n(\text{TN}_{ij}^a \text{TP}_{ij}^b \text{V}_{ij}^c [1 + \text{P}]_{ij}^d) \tag{1}$$

In which  $\text{Chl-a}_{ij}$  is the concentration of Chl-a for reservoir  $i$  corresponding to sample  $j$ . The coefficients a, b, c, and d can assume negative or positive numerical solutions according to the influence of each parameter on the concentration of Chl-a. Note that TN, TP, and V are always higher than zero. However, since  $P=0$  during the dry periods, the last term  $[1 + P]$  was adopted as a sum with 1 to prevent null results in Eq. 1. In this case, for  $P=0$ , the term becomes 1, meaning no precipitation effect. On the other hand, the higher the value of P, the higher the effect of precipitation in Eq. 1. To identify the most relevant parameters in the concentration of Chl-a in the reservoirs, simple linear regression models were developed to obtain the coefficient of determination ( $R^2$ ) (Eq. 2) between Chl-a and the nutrients TN and TP (Chl-a:TN and Chl-a:TP) and the hydroclimatic variables V and P (Chl-a:V and Chl-a:P).

### Model performance

The developed empirical models were evaluated according to the coefficient of determination ( $R^2$ ) (Eq. 2), which quantifies how much the dependent variable is determined by the independent variables in terms of the proportion of variance (Chicco et al. 2021). These coefficients were classified into four groups according to the performance evaluation criteria for statistical performance measures for watersheds proposed by Moriasi et al. (2015), considering nitrogen as the base parameter (which may be easier to predict than Chl-a): Unsatisfactory (U) ( $R^2 \leq 0.3$ ), Satisfactory (S) ( $0.3 < R^2 \leq 0.6$ ), Good (G) ( $0.6 < R^2 \leq 0.7$ ), and Very Good (V) ( $R^2 > 0.7$ ). In addition, the performance of the model was further evaluated using the root mean square error (RMSE) (Eq. 3), mean absolute error (MAE) (Eq. 4), and percent bias (PBIAS) (Eq. 5).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \tag{3}$$

$$\text{MAE} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \tag{4}$$

$$\text{PBIAS} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{\sum_{i=1}^n (y_i)} \tag{5}$$

In which  $n$  is the number of observations in the dataset,  $y$  is the observed Chl-a,  $\hat{y}$  is the predicted Chl-a, and  $\bar{y}$  is the mean observed Chl-a.

### Sensitivity analysis and application of results

The sensitivity analysis was carried out by testing input values in the empirical equations of the largest strategic reservoirs in the state of Ceará: Castanhão/Médio Jaguaribe and Orós/Alto Jaguaribe, and assessing the influence of water quality class changes on Chl-a concentration. For this, the maximum values of each class presented in Table 1 were associated with the mean values of the parameters in the dataset used for the development of each equation, resulting in five categories: categories 4, 3, 2, and 1 (represent the association of a variable with a concentration in classes 4, 3, 2, and 1 to the mean values of the other input variables) and Category 0 (represents the combination of the average of all parameters). To help visualize the effects of Chl-a modeling contribution to water quality management, the most favorable and unfavorable scenarios concerning the modeled Chl-a concentration for the Castanhão/Médio Jaguaribe and Orós/Alto Jaguaribe strategic reservoirs were identified. All possible combinations among model components were simulated using the maximum values of each class defined in Table 1 for each reservoir.

## Results

### Limnological and spatio-temporal analysis of variables

The mean and standard deviation values for the parameters TN, TP, Chl-a, V, and P in the studied reservoirs were, respectively,  $1.949 (\pm 1.056) \text{ mg L}^{-1}$ ,  $0.124 (\pm 0.083) \text{ mg L}^{-1}$ ,  $47.624 (\pm 46.988) \mu\text{g L}^{-1}$ ,  $36.059 (\pm 20.161) \%$ , and  $2.025 (\pm 0.775) \text{ mm}$ . There was a wide variation in the mean concentration values of TN ( $0.659\text{--}2.673 \text{ mg L}^{-1}$ ), TP ( $0.025\text{--}0.189 \text{ mg L}^{-1}$ ), and Chl-a ( $15.555\text{--}53.644 \mu\text{g L}^{-1}$ ) within the watersheds. The highest mean concentrations of TN and Chl-a were identified in the Banabuiú (BN) basin, while the highest TP level was identified in the Sertões de Crateús (SC) basin.

The spatiotemporal variability of the parameter means (Figure S1, supplementary material) during periods P1, P2, and P3 can be observed through the color scale map shown in Fig. 2, which indicates parameter classification in the framing classes established in Table 1 for each basin. The statistical analysis resulted in a significant  $p$  value ( $< 0.05$ ) to support differences in the mean concentration of TP and TN among P1, P2, and P3 for all basins except Serra da Ibiapaba (SI). Regarding Chl-a, significant differences within the periods were identified for 58% of the analyzed basins. As for the hydroclimatic variables, statistical differences among the three periods were shown in 92% and 75% of the basins under study. During P1 and P3, the reservoirs had higher volumetric percentages and higher mean annual precipitation (860 and 886 mm/year), with a mean volume of 42.38% and 58.51% and mean daily precipitation of  $1.747 (\pm 0.160)$  and  $1.642 (\pm 0.163)$  mm. However, during P2, V was reduced to 24.21%, with approximately 30% of the reservoirs with a mean volume lower than 15%. Despite the mean annual precipitation in this period being lower than the others (613 mm), P was higher ( $2.503 \pm 0.123$ ), indicating rainfall events of greater intensity distributed during long periods.

The mean and standard deviation values of TN, TP, and Chl-a during P1 were  $1.062 (\pm 0.984) \text{ mg L}^{-1}$ ,  $0.111 (\pm 0.160) \text{ mg L}^{-1}$ , and  $22.896 (\pm 32.894) \mu\text{g L}^{-1}$ . In the following period (P2), nutrient and Chl-a concentrations increased to  $2.421 (\pm 2.509) \text{ mg L}^{-1}$ ,  $0.137 (\pm 0.163) \text{ mg L}^{-1}$ , and  $62,401 (\pm 102.326) \mu\text{g L}^{-1}$ . Likewise, during P3, where volume accumulation conditions improved, the mean concentrations were  $1.654 (\pm 1.874) \text{ mg L}^{-1}$ ,  $0.101 (\pm 0.123) \text{ mg L}^{-1}$  and  $36.064 (\pm 51.295) \mu\text{g L}^{-1}$ . From period P1 to P2, as mean percent volume decreased in all basins and mean P increased in 67%, mean values of NT, PT, and Chl-a increased in 92%, 75%, and 100% of the basins, respectively. Similarly, from P2 to P3, as

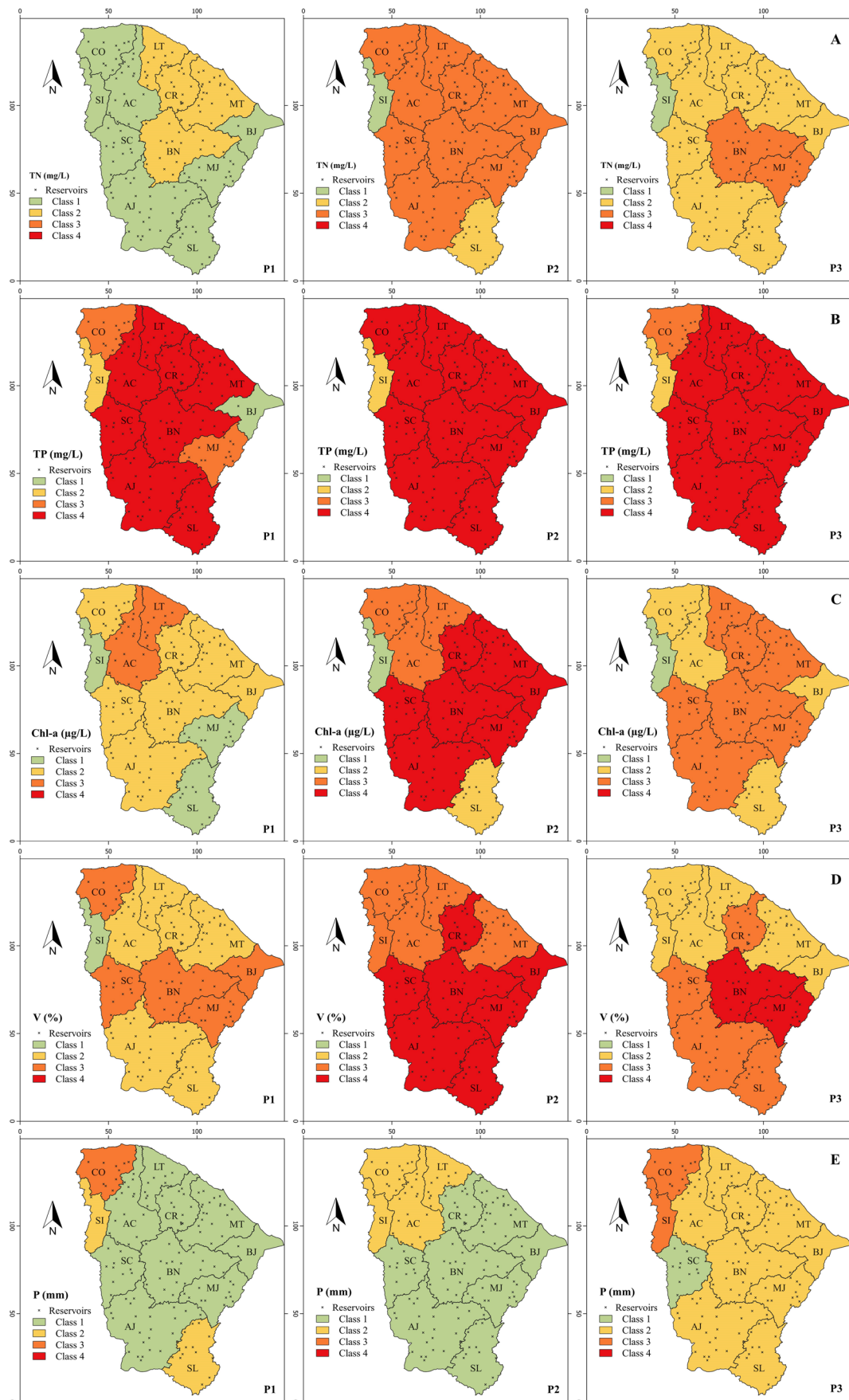
precipitation and volume increased in most basins (92%), NT, PT, and Chl-a mean values were reduced in 100%, 84%, and 92% of the studied basins.

Time series of the studied variables for the reservoirs Castanhão and Orós (see Figure S2 for the time series of the larger reservoirs in each watershed) are shown in Fig. 3. These reservoirs differ from the others due to their high volumetric capacity of  $6700 \text{ hm}^3$  and  $1940 \text{ hm}^3$ , respectively, being the largest strategic reservoirs in the state. Mann–Kendall's non-parametric trend test suggested an upward trend ( $p$  value  $< 0.05$ ;  $Z > 0$ ) in the nutrient time series data while a downward trend ( $p$  value  $< 0.05$ ;  $Z < 0$ ) is observed in the volume database considering the three studied periods. Therefore, although variable, the concentration of nutrients and Chl-a in these reservoirs showed an increasing trend while the volume in the reservoir progressively decreased over time.

### Chlorophyll-a modeling

To test the predictive capacity of each input, linear regression models were employed to establish the parameters' correlation to Chl-a. The variable with the highest mean  $R^2$  was TN ( $0.400 \pm 0.27$ ), followed by TP ( $0.260 \pm 0.228$ ), V ( $0.204 \pm 0.157$ ), and, finally, P ( $0.053 \pm 0.090$ ). Using the performance evaluation criteria proposed by Moriasi et al. (2015), the highest number of correlations considered at least satisfactory ( $R^2 > 0.3$ ) was between Chl-a and TN in 57% ( $n = 86$ ) of the reservoirs, followed by TP with 41% ( $n = 61$ ). For most data, V and P presented unsatisfactory correlations, with only 27% ( $n = 40$ ) and 3% ( $n = 4$ ) of the reservoirs with satisfactory  $R^2$ , respectively. These results are illustrated in Table 2 for the highest volumetric capacity reservoirs in each studied basin and listed for all the 150 reservoirs in Table S2 (supplementary material).

The empirical models developed to predict Chl-a used four input variables: TN, TP, V, and P. Due to the very different characteristics among the studied reservoirs, such as total capacity, hydrographic basin type (rural or urban), climatic conditions, etc., the development of general models (i.e., grouping datasets into similar concentrations, hydrographic basins or into single dataset) did not result in significant performances. Therefore, individual models were developed for each reservoir, preserving their intrinsic characteristics. Table 2 presents the resulting empirical equations and evaluation metrics ( $R^2$ , RMSE, MAE, and PBIAS) for the reservoirs with the highest volumetric capacity in each studied basin. Table S2 (supplementary material) lists these results for the 150 evaluated reservoirs. The mean measured ( $45.637 \mu\text{g L}^{-1}$ ) and modeled ( $44.477 \mu\text{g L}^{-1}$ ) Chl-a values were very similar, considering all dataset. Accordingly, mean differences of less than 10% were identified in 82% of the reservoirs ( $n = 122$ ). Since the amount of data



**Fig. 2** TN (A), TP (B), Chl-a (C), V (D), and P (E) mean value classifications according to Table 1 framing classes during the periods P1 (2008–2012), P2 (2013–2017), and P3 (2018–2021)

per reservoir is limited, applying a more robust validation model of the empirical equations (through a test dataset, for example) was not feasible. Thus, model validation was performed in a simplified way, comparing the measured and modeled Chl-a throughout the study period (see Figure S3, supplementary material).

Following the performance evaluation criteria suggested by Moriassi et al. (2015), all models were Satisfactory ( $R^2 > 0.3$ ), with 69% (52) of the reservoirs with Good or Very good performance ( $R^2 > 0.6$ ). The mean  $R^2$  for all models was 0.699 (RMSE = 17.259 and MAE = 13.581  $\mu\text{g L}^{-1}$ ). In addition, all developed models showed statistically significant  $R^2$  ( $p < 0.01$ ). Comparisons of modeled versus observed time series of Chl-a for the largest reservoir of each watershed are shown in Fig. 4 (see Figure S4 for the 150 reservoirs). In general, the estimated Chl-a concentration followed well the temporal behavior of the data, noting that, even in models with lower statistical performance, such as the Jaburu I/SI ( $R^2 = 0.32$ ) and Orós/AJ ( $R^2 = 0.51$ ), the model showed consistency in the prediction of concentration peaks. Thus, the models proved to be adequate for evaluating the temporal variability of Chl-a concentration in the studied reservoirs. During the wet season (P1), blooms are distributed evenly throughout the year. However, in P2 and P3, marked by lower accumulation volumes and high variability in precipitation events, most concentration peaks were identified between January and May (mainly in April and March), which generally comprises 80% of the state's annual precipitation (Campos 2011), and in November, which has the highest mean monthly TN observed (2.19  $\text{mg L}^{-1}$ ).

## Discussion

### Spatiotemporal patterns of variables

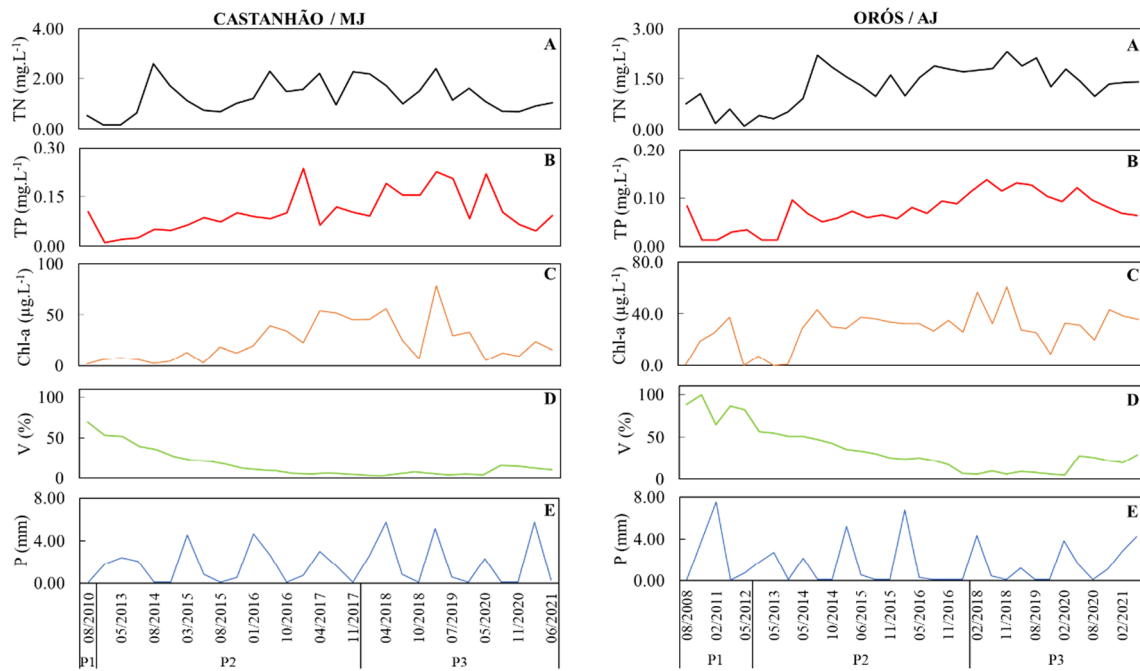
The results showed that TN, TP, and Chl-a were highly variable at spatiotemporal scale. However, the concentrations were within the ranges reported in the literature for reservoirs in the Brazilian Northeastern (Cortez et al. 2017; Wiegand et al. 2021; Rocha and Lima Neto 2022; Rocha et al. 2022). The worse water quality identified in BN and SC can be attributed to several factors. For example, BN is the basin with the highest density of reservoirs among those evaluated. In these types of basins, smaller reservoirs that are usually empty at the beginning of the rainy season favor significant sediment retention and intensify its transport to downstream reservoirs due to inflow increase (Rabelo et al. 2021). In addition, the existence of several smaller reservoirs

with lower hydrological efficiency upstream of strategic reservoirs leads to volume reduction; BN, for example, reached 0.7% of its volumetric capacity during the dry season (P2) (Lima Neto et al. 2011; Malveira et al. 2012; Mamede et al. 2018; Freire et al. 2022). According to Schönbrunner et al. (2012), repeated drying and wetting episodes result in elevated phosphorus release due to enhanced mineralization rates and reduction of iron hydroxide, especially when drying periods lead to a significant (80%) water content reduction (Bai et al. 2019). As for SC, the high concentrations can be attributed to the reservoir monitoring site being located immediately downstream of stabilization pond systems (Freire et al. 2021, 2022).

The temporal distribution of the variables showed that, in most basins, the reservoir volume reduction and the increase in sporadic precipitation events of greater intensity caused an increase in nutrient concentration and changes in framing classes during the drought period (P2) and in the subsequent classes during the drought period (P2) and in the subsequent period (P3), which was also evidenced in studies in other regions (Bortoletto et al. 2015; Cruz et al. 2019a, b). Especially in the state of Ceará, seasonal volume variability is highly influenced by changes in precipitation levels, where, due to the tropical/semiarid condition inflow is completely interrupted during dry periods (Cavalcante et al. 2018; Rocha and Lima Neto 2021b). In summary, as expected, drought events cause rapid deterioration of water quality (Cavalcante et al. 2021; Rocha and Lima Neto 2022).

In contrast to the other basins, SL and SI showed the lowest averages of nutrient concentration in the three evaluated periods. In fact, better water quality in these basins may be associated with regional groundwater flow and reservoir density, respectively. The SL basin has the unique sedimentary geological formations in the state, which provides significant groundwater reserves. Studies have shown that isotopic similarities between wells and small reservoirs allow the interaction between surface water and groundwater, with water recharge and increased oxygen availability, significantly reducing nutrient loads, especially total phosphorus in tropical reservoirs (Alberto et al. 2004; Machado et al. 2004; Lewandowski et al. 2015; Moura et al. 2020; Wiegand et al. 2021). On the other hand, due to its sedimentary hydrogeological characteristic, the SI hydrographic region has fewer water bodies than the other studied basins (Ceará 2022b). As mentioned earlier, the high density of reservoirs is a characteristic that potentially contributes to the deterioration of water quality since it favors the retention of sediments and the reduction of inflow to downstream reservoirs (Lima Neto et al. 2011; Mamede et al. 2018).

In the largest reservoirs under study (Castanhão and Orós), the high TP levels observed (0,104  $\text{mg L}^{-1}$  for both reservoirs) may be related to the significant input of external loads of nutrients and sediments from non-point sources



**Fig. 3** Time series plot of total nitrogen (A), total phosphorus (B), chlorophyll-a (C), volumetric percentage (D), and daily precipitation (E) for the strategic reservoirs Castanhão (MJ) and Orós (AJ) during the periods P1 (2008–2012), P2 (2013–2017), and P3 (2018–2021)

**Table 2** Mean coefficients of determination ( $R^2$ ) resulting from simple linear regression between Chl-a and TN, TP, V, and P. Developed empirical equations and their respective performance metrics for the largest capacity reservoirs in each hydrographic region under study are also indicated

WS <sup>1</sup>	R <sup>2</sup>	N <sup>3</sup>	R <sup>2</sup> [Chl-a:f]				Chl-a = n(TN <sup>a</sup> TP <sup>b</sup> V <sup>c</sup> [1 + P/Pmax] <sup>d</sup> )									
			TN	TP	V	P	R <sup>2</sup>	MAE	RMSE	PBIAS	P <sup>4</sup>	n	a	b	c	d
AC	2	34	0.56	0.55	0.46	0.00	0.86	18.64	25.99	-0.80%	V	871	-0.05	0.24	-0.75	-0.37
<b>AJ</b>	<b>30</b>	<b>32</b>	<b>0.43</b>	<b>0.06</b>	<b>0.25</b>	<b>0.01</b>	<b>0.51</b>	<b>8.50</b>	<b>10.32</b>	<b>-0.47%</b>	<b>S</b>	<b>15</b>	<b>0.79</b>	<b>-0.19</b>	<b>-0.04</b>	<b>0.48</b>
BJ	40	21	0.73	0.86	0.09	0.04	0.98	7.20	9.91	4.46%	V	3,950	-0.86	1.69	0.05	-3.48
BN	41	24	0.06	0.00	0.17	0.21	0.71	8.37	9.86	5.15%	V	17	0.04	-0.45	-0.45	-3.51
CO	63	26	0.81	0.25	0.51	0.03	0.87	6.17	7.55	-1.58%	V	66	1.25	-0.21	-0.50	0.52
CR	76	41	0.76	0.43	0.23	0.03	0.79	13.26	16.21	0.30%	V	50	0.53	0.13	-0.05	-0.59
LT	84	26	0.14	0.00	0.06	0.06	0.81	14.68	17.14	2.72%	V	0.07	2.38	-0.58	0.95	0.32
<b>MJ</b>	<b>95</b>	<b>29</b>	<b>0.34</b>	<b>0.16</b>	<b>0.38</b>	<b>0.20</b>	<b>0.79</b>	<b>7.00</b>	<b>8.94</b>	<b>-0.91%</b>	<b>V</b>	<b>66</b>	<b>0.34</b>	<b>0.05</b>	<b>-0.58</b>	<b>0.97</b>
MT	120	39	0.19	0.19	0.06	0.00	0.61	12.50	15.05	-0.75%	G	278	0.43	0.39	-0.31	-0.30
SC	131	29	0.59	0.28	0.10	0.02	0.89	15.45	21.95	6.15%	V	162	0.59	0.85	-0.03	-2.13
SI	136	35	0.06	0.02	0.21	0.01	0.32	0.80	1.01	0.04%	S	14	-0.11	0.07	-0.37	-0.04
SL	137	36	0.70	0.08	0.38	0.05	0.88	14.60	17.95	1.22%	V	356	0.66	0.18	-0.63	-0.12

Bold values represent the state's largest strategic reservoirs in study

<sup>1</sup>Watershed

<sup>2</sup>Reservoir name: 2, Araras; 30, Orós; 40, Snt Ant. De Russas; 41, Banabuiú; 63, Itaúna; 76, Pentecoste; 84, Missi; 95, Castanhão; 120, Pacoti; 131, Flor Do Campo; 136, Jaburu I; 137, Atalho

<sup>3</sup>N=number of samples

<sup>4</sup>Statistic performance: V, Very good; G, Good; S, Satisfactory; U, Unsatisfactory



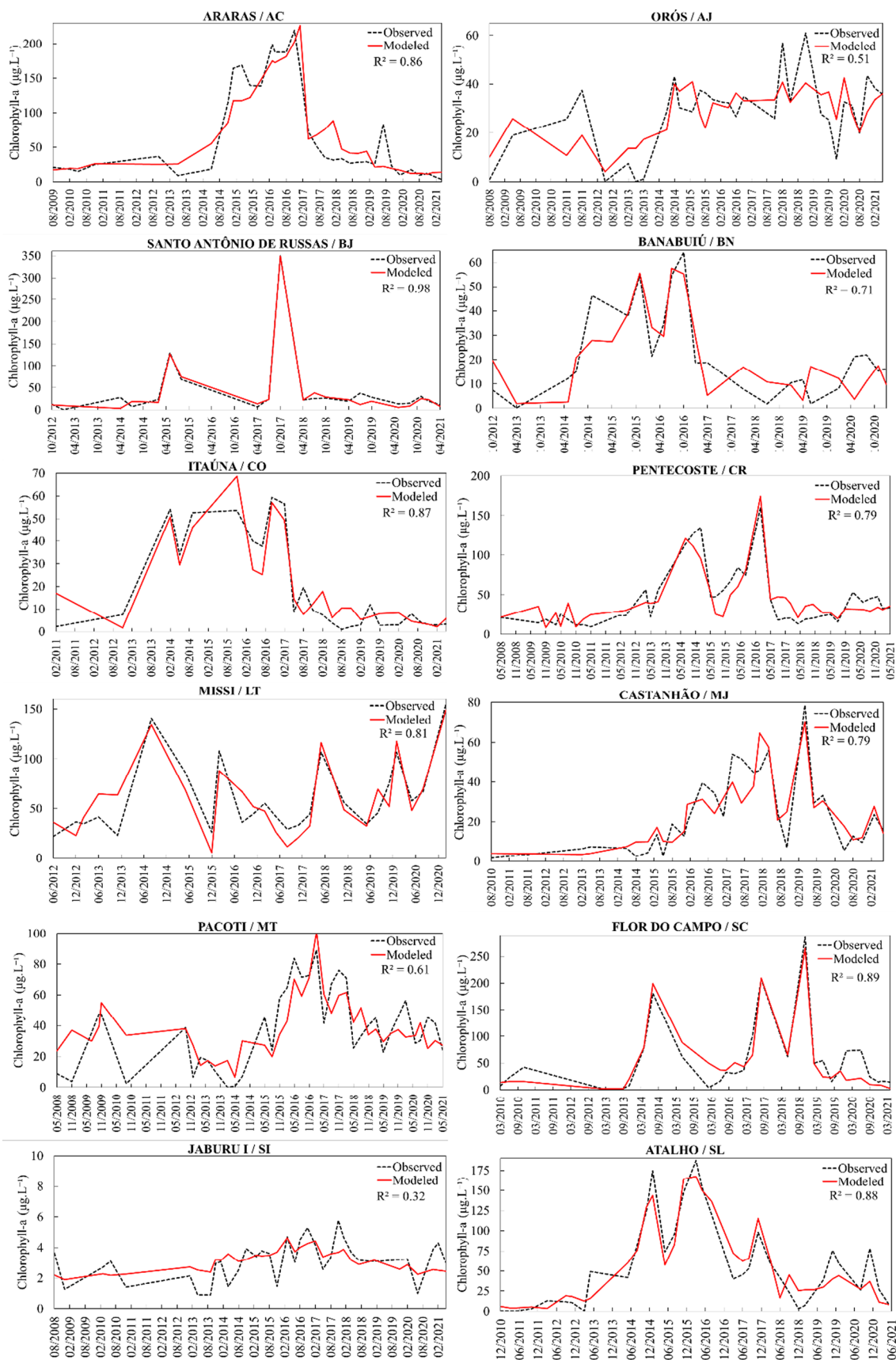


Fig. 4 Time series plot comparison between modeled (red line) and measured (dashed black line) chlorophyll-a concentrations for all reservoirs under study

from rural areas of greater extension ( $> 24,000 \text{ km}^2$ ); such basins represent the most relevant irrigated cultivation areas in the state (Rocha and Lima Neto 2022). In previous studies on these reservoirs, high TP levels were associated by Raulino et al. (2021) to the volume decrease caused by inflow reduction, impacting the natural self-depuration of the rivers, increasing the nutrient transport and intensifying the trophic state. Moreover, similar TP concentrations were identified in other studies in the same region by Figueiredo and Becker (2018) (0.021–0.147), Rocha et al. (2020) (0.118–0.302  $\text{mg L}^{-1}$ ), and Rocha and Lima Neto (2020) (0.04 and 0.59  $\text{mg L}^{-1}$ ), while in other non-tropical regions, less affected by high seasonal and annual variability of the water level, as well as the lower density of reservoirs, the values were significantly lower: 0.001–0.02 (Chen et al. 2015), 0.004–0.0139 (Hennemann and Petrucio 2016), and 0.008–0.009 (Jargal et al. 2021).

### Correlation between Chl-a, nutrients, and hydroclimatic variables

The regression results showed that TN was the variable with the best ability to predict Chl-a levels [58% ( $n=87$ ) of the reservoirs], resulting in a higher  $R^2$  than all other parameters. Furthermore, in 73% ( $n=110$ ) of the reservoirs, TN better explained the variability of Chl-a than TP. Contrastingly, because it is considered the limiting nutrient for eutrophication and cyanobacterial blooms, TP has been adopted as a representative variable of water quality and eutrophication in lakes and reservoirs worldwide (Dillon and Rigler 1974; Xu et al. 2020; H.G. Kim et al. 2021a, b; Raulino et al. 2021; Zhang et al. 2022). However, the results observed for most reservoirs are consistent with the studies by Canfield (1983), which analyzed data from 223 lakes in Florida, and identified, through simple empirical equations, that TN was the main predictor of Chl-a in hypereutrophic lakes. TN was also the preponderant factor for algae production in 60% of the reservoirs studied by Wiegand et al. (2020) in the state of Ceará, being the nutrient that presented the best correlation with the concentration of Chl-a. These authors also reported that growth limitation was predominantly by TN during the wet period (2008–2012), shifting to TP during the dry period (2013–2017). Other studies also reported TN as the main Chl-a driver in temperate lakes and reservoirs worldwide (Bilgin and Bayraktar 2021; Kim et al. 2021a, b; Stepanova 2021; Xu et al. 2022; Zou et al. 2022). This limiting nutrient shifting effect may be associated with massive TP loads in these reservoirs. Observe that the studied reservoirs have been receiving, for decades, effluents from livestock, agriculture, and fish farming that are richer in phosphorus than nitrogen (Wiegand et al. 2020). Additionally, internal TP loading significantly contributes to the increase in TP concentrations (Rocha and Lima Neto 2022). In case of elevated

phosphorus concentrations, planktonic nitrogen use may exceed inputs and deplete nitrogen supply in the trophogenic zone, decreasing the TN/TP ratio in the water column (Ding et al. 2018). As a result, the limiting status transfers from TP limitation to TN limitation, with this balance regulating the phytoplankton growth (Feng et al. 2020).

In the regression models developed in this research, the least influential variable was daily precipitation. Only four reservoirs showed satisfactory  $R^2$ , and all other reservoir adjustments were statistically insignificant ( $p > 0.05$ ). In previous studies, Hecht et al. (2022) evaluated the relative effects of climate change on algae blooms, identifying that blooms were sensitive to changes in precipitation, which could increase nutrient load or prevent blooms depending on the previous conditions of the aquatic environment. However, other studies have also concluded that assessing the isolated effects of precipitation on Chl-a levels can be a complex process, once while the increase in extreme precipitation events can increase external loads due to nutrient drag, it can also increase river flow, which can influence nutrient dilution, decrease water temperature, reduce water and constituents' residence time, and restrict water flow (Mamede et al. 2018; Huang et al. 2020; Wiegand et al. 2021; Freire et al. 2022; Hecht et al. 2022). In general, the presence of significant correlations between Chl-a and the model parameters showed that the dynamics of Chl-a in the reservoirs may not be dictated by only one independent variable, being necessary to consider that the predictor variables, when combined, may present complementary information, as they are often correlated (Reynolds 1992; Paerl et al. 2016; Mesquita et al. 2020).

### Chl-a response to the model input variables

The results showed that the empirical models with the combination of hydroclimatic and nutrients input variables performed well to predict Chl-a. The models mean  $R^2$  (about 0.70) was superior to Chl-a prediction models identified in previous studies by Rocha et al. (2020) ( $R^2=0.34$ ), Rotta et al. (2021) ( $R^2=0.64$ ), Carvalho et al. (2022) ( $R^2=0.52$ ), and Ventura et al. (2022) ( $R^2=0.52$ ) in the studied region, and similar to the performance of more complex methods by Liu et al. (2016) ( $R^2=0.72$ ), Lopes et al. (2021) ( $R^2=0.76$ ), Gidudu et al. (2021) ( $R^2=0.72$ ), Aranha et al. (2022) ( $R^2=0.77$ ), and Lu et al. (2022) ( $R^2=0.75$ ).

Furthermore, the input variables have different influences on the outcome of the models. For most models, Chl-a is positively related to TN and TP, which indicates that the increase in nutrient availability in the water column favors the increase in phytoplankton biomass, as expected (Paerl et al. 2016; Mamun and An 2017). However, negative exponents were observed for TN and TP in 22% and 27% of the cases, respectively, occurring simultaneously in 6% of the reservoirs. Previous studies have

shown this effect. As reported by Wiegand et al. (2021), for 65 reservoirs in the same region, the limiting nutrient shifted according to the observation period, with TN being predominant during the wet period and TP during the dry period. In other studies, Chl-a to nutrient negative relation was attributed to limited light availability for phytoplankton growth due to increased suspended particles in the water. Since intensive fish farming and artisanal fishing occur, respectively, in 56% and 100% of these reservoirs (Ceará 2018), high concentration of suspended particles in the water column may occur as a result of the bioturbation behavior associated with the fish species commonly produced in the studied reservoirs (Wiegand et al. 2020). It is also worth mentioning that, in cases where the two nutrients presented negative exponents, the V and P exponents were higher, indicating that, in these cases, the hydroclimatic variables were more influential in the prediction of Chl-a.

Regarding hydroclimatic parameters, most reservoirs (67%) had a negative exponent for volume, indicating a reduction in the concentration of Chl-a during periods of greater accumulation and lower nutrient concentration. The increase in volume had the opposite effect in 33% of the cases. Once the sedimentary concentration of nutrients may increase with reservoir age (Rocha and Lima Neto 2021a), this effect was investigated for the reservoirs with positive volume exponent. However, no clear trend was identified between Chl-a and reservoir age. The investigation of the complexity of the processes that occur as volume increases, such as the counterbalancing effects of nutrient dilution and water column stratification, which results in TP release from anoxic sediments (Wang et al. 2016; Moura et al. 2020) could improve the understanding of the positive effect volume had on Chl-a in this study. However, data on these complex determinants were not available, justifying the absence of a simple relationship explaining this effect.

The increase in Chl-a is dictated in 49% of the reservoirs by the increase and in 51% by the reduction of daily precipitation. In previous studies, Freire et al. (2022), investigating the influence of precipitation on nutrient concentration in the Ceará basins, also identified positive and negative relationships between TP and P in different watersheds. During precipitation events, surface runoff increases, and more sediment is transported, resulting in an excessive nutrient load (Cruz et al. 2019a, b; Lira et al. 2020). Likewise, the increase in precipitation may imply an increase in the inflow into the reservoirs, which may cause a decrease in concentration through the dilution of nutrients (Tang et al. 2019; Lima Neto et al. 2022). The negative exponents in this variable suggest that the “dilution effect” of the inflow (rainfall result) in some watersheds outweighs the “enrichment effect” of the nutrient concentration in the reservoirs (Rocha and Lima Neto 2021a).

In general, the reduction in nutrient load (mainly TP) due to the dilution effect occurs when the predominant sources of pollution are punctual. However, in the case of predominantly diffuse sources, the release of TP retained in the sediments causes an increase in the load proportional to the inflow (Coffey et al. 2019; Freire et al. 2022; Lima Neto et al. 2022). In fact, the reservoirs in which increased precipitation intensity had a nutrient “enrichment effect” are mainly located (75%) in predominantly rural basins, where non-point sources of pollution are dominant, originating from soil and agriculture. This behavior was confirmed by Rocha and Lima Neto (2021a), who reported that the fitted TP concentration-flow relationship is related to the pollution source types: in rural basins dominated by non-point sources, the curves presented a “U-shaped” behavior (decay patterns and subsequent increase with flow), while in urban basins dominated by point sources, a dilution pattern (decay of concentration with the flow) prevailed.

It is worth mentioning, however, that 26 reservoirs (located mainly in the MT, BN, and AJ basins) presented a different fitting: positive exponent for the variable V and negative for P, which implies that the concentration of Chl-a increases with the increase in accumulated volume and decreases of precipitation. In reservoirs that face considerable deposition of nutrient-enriched sediments, conditions of high water temperatures favor stratification of the water column and rapid organic degradation, often forcing anoxic conditions on the bottom sediment, promoting a more significant release of phosphorus to the water column (Moura et al. 2020; Lima Neto et al. 2022). In addition, in most of these reservoirs (74%), significant variations were observed in the volumetric percentage, and the mean accumulated volume was higher than in the other reservoirs during the dry period. Similar results were observed by Liu et al. (2015), Wang et al. (2021), and Wu et al. (2019, 2022). Continuous transitioning processes between low and high water levels can cause resuspension of accumulated material during periods of lower volume and higher wind shear, which, associated with the watershed use and occupation characteristics, can result in physical-chemicals variations of the water column and increased concentration of nutrients (Geraldés and Boavida 2005; Cruz-Ramírez et al. 2019; Rocha and Lima Neto 2022).

Finally, the analysis of Chl-a blooms through the investigation of interannual variation patterns in the time series of the 150 reservoirs under study revealed that the occurrence of Chl-a peaks is mainly susceptible to changes in extreme events of precipitation. However, the complex interaction between nutrient loading and climate variability events makes it difficult to suggest a single parameter responsible for controlling algae blooms in reservoirs (Wilkinson et al. 2022). Previous studies have reported that extreme precipitation events followed by periods of drought are the ideal

scenario for blooms. During these periods, when temperatures and water stratification are at their maximum, heavy rainfall can promote a significant increase in harmful algae blooms through increased nutrient loading, particularly in trophic environments (Michalak et al. 2013; Sinha et al. 2017; Coffey et al. 2019; Wilkinson et al. 2022; Zou et al. 2022). However, precipitation’s influence on concentration peaks is difficult to generalize. In addition to depending on the intensity and frequency of rainfall events (Ho and Michalak 2020), it also depends on the initial conditions of the reservoir (Carvalho et al. 2022), the behavior between nutrient concentration and inflow (Rocha and Lima Neto 2021a; Lima Neto et al. 2022) and other meteorological variables (wind speed, daily temperatures, evaporation rates, among others) (Woolway and Merchant 2019; Woolway et al. 2020).

**Model sensitivity and assessment of water quality improvement scenarios**

Sensitivity analysis was performed using the proposed models for Castanhão (MJ) and Orós (AJ) to evaluate the influence of the increase/reduction of a variable in the concentration of Chl-a using the classification range values proposed in Table 1. As shown in Table 3, the reservoirs’ average operating conditions (category 0) simulated using the mean concentration values for TN, TP, Chl-a, V, and P showed that both reservoirs had similar operating conditions. In this category, all input variables were classified into the same class, except for volume, which was lower for Castanhão (C4) than Orós (C3).

The simulations allowed to examine the effects of nutrient reduction in order to assess different strategies to improve

water quality. For example, Chl-a concentration has different responses in each reservoir. Orós’s model showed lower sensitivity to the input’s variability than Castanhão’s model. While for Castanhão changes in Chl-a framing class happened in seven different scenarios (five referring to Chl-a increase and two to Chl-a reduction), the model proposed for Orós only presented three scenarios in which Chl-a class is modified (two for Chl-a increase and one for Chl-a decrease).

Regarding the response of Chl-a concentration to hydro-climatic variables, both reservoirs were influenced by the effect of precipitation. For Castanhão, extreme concentrations of Chl-a (> 30 µg L<sup>-1</sup>, classes 3 and 4) were obtained for all scenarios of increased P. As for Orós, changes in Chl-a class were only observed for C4 precipitation values. Similarly, in Castanhão, the proposed model predicted that only a 50% or 75% increase in volume (change from C4 to C2/C1) would promote a change of Chl-a class from C2 to C1, while Orós did not show significant sensitivity to any volume change. The greater sensitivity of Castanhão’s model to P, compared to Orós, may be attributed to its watershed’s sewage treatment connection, which, according to Freire et al. (2022), is the worst in the state with a percentage of only 4.2%. In addition, Castanhão dataset showed more significant episodes of extreme water content reduction. In 50% of the data, the reservoir volume was less than 10%, while the same water content was observed in only 9% of Orós’ measurements.

Furthermore, the results showed that changes in TN framing classes promoted Chl-a changes in both reservoirs. However, no TP scenario simulation promoted changes in the Chl-a

**Table 3** Sensitivity of Chl-a to the input variables TN, TP, V, and P. C1, C2, C3, and C4 represent the maximum values for each class defined in Table 1. Category 0 represents the reservoir mean input values. Categories 4, 3, 2, and 1 represent, respectively, the combination of a variable with concentration in classes C4, C3, C2, and C1 with the mean values of the other input variables

CATEGORIES	CASTANHÃO / MJ					ORÓS / AJ					
	TN	TP	V	P	Chl-a	TN	TP	V	P	Chl-a	
	0	C2	C4	C4	C1	C2	0	C2	C4	C3	C1
4	C4	C4	C4	C1	C3	4	C4	C4	C3	C1	C4
	C2	C4	C4	C1	C2	4	C2	C4	C3	C1	C3
	C2	C4	C4	C1	C2	4	C2	C4	C4	C1	C3
	C2	C4	C4	C4	C4	4	C2	C4	C3	C4	C4
3	C3	C4	C4	C1	C3	3	C3	C4	C4	C2	C3
	C2	C3	C4	C1	C2	3	C2	C3	C3	C1	C3
	C2	C4	C3	C1	C2	3	C2	C4	C3	C1	C3
	C2	C4	C4	C3	C4	3	C2	C4	C3	C3	C3
2	C2	C4	C4	C1	C2	2	C2	C4	C3	C1	C3
	C2	C2	C4	C1	C2	2	C2	C2	C3	C1	C3
	C2	C4	C2	C1	C1	2	C2	C4	C2	C1	C3
	C2	C4	C4	C2	C3	2	C2	C4	C3	C2	C3
1	C1	C4	C4	C1	C2	1	C1	C4	C3	C1	C2
	C2	C1	C4	C1	C2	1	C2	C1	C3	C1	C3
	C2	C4	C1	C1	C1	1	C2	C4	C1	C1	C3
	C2	C4	C4	C1	C2	1	C2	C4	C3	C1	C3

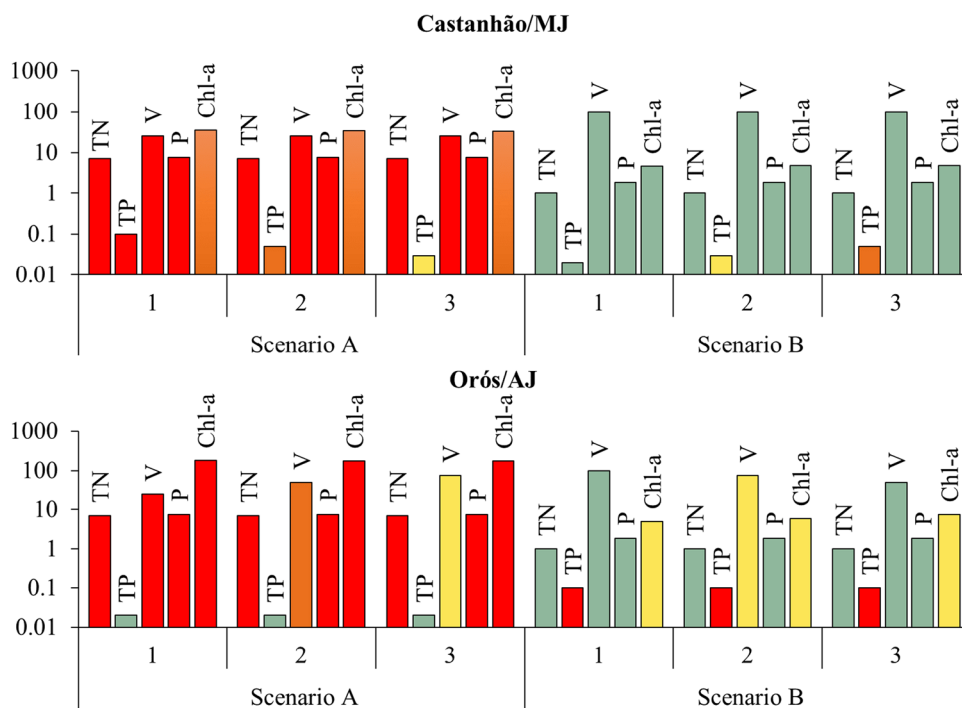
framing class in Castanhão or Orós. For Castanhão, increases in TN concentrations to classes C3 and C4 promoted increases in Chl-a class to C3. However, TN reduction scenarios for this reservoir did not promote Chl-a class improvement, remaining as C2 even for TN's lowest simulated value (C1). As for Orós, the only Chl-a framing class improvement scenario (C2 to C1) happens with TN concentration reduction to the minimum value (C1). In this perspective, while there are aquatic environments where exclusive phosphorus control will significantly reduce algal biomass, considerable reductions in phosphorus concentrations can be made in hypereutrophic environments without significantly reducing Chl-a values. In the absence of simultaneous nitrogen control, the TN:TP ratio can increase significantly, resulting in an increase rather than a decrease in algae biomass (Canfield 1983; Harris et al. 2014).

To test the model's ability, a wide range of water quality scenarios were simulated, considering all plausible combinations of the input variables concentrations in the framing classes presented in Table 1 (see Figure S5 and Table S3, supplementary material). Figure 5 shows the six selected simulations representing the most unfavorable (A), and favorable (B) scenarios concerning Chl-a concentration. In scenarios A1, A2, and A3, the worst Chl-a concentrations in both reservoirs are simulated. In scenario A1, these concentrations occurred due to the association of high nutrient concentrations, critical volume, and high daily precipitation. As observed previously, the improvement in TP concentration did not promote any changes in Chl-a framing class of these reservoirs.

The most favorable scenarios, observed through B1, B2, and B3, are conditioned to the occurrence of low levels of

TN and P in both reservoirs. Under these conditions, neither the increase in TP concentrations nor volume reduction promoted Chl-a framing class changes. Moreover, for Castanhão, the remaining simulations (Figure S5, supplementary material) showed that even in scenarios of low volumetric percentages (C4) and high precipitation levels (C3), Chl-a concentrations of class 2 can be obtained through the reduction of TN, regardless of the TP content. However, for Orós, in all simulated scenarios (49) in which there is a combination of high TN (C3 and C4) and low TP (C1 and C2), the modeled Chl-a concentration falls into Class 4 ( $> 60 \mu\text{g L}^{-1}$ ). The occurrence of increased blooms under similar conditions was reported in other studies, where in lakes and reservoirs with high concentrations of nitrogen, TN became the limiting nutrient, triggering the dominance of toxic cyanobacteria (Smith 1983; Prairie et al. 1989; Bachmann et al. 2003; González Sagrario et al. 2005; Yan et al. 2016; Yu et al. 2022). Nutrient management strategies aimed at exclusively reducing TP load can cause an imbalance between TN and TP cycling in aquatic environments, interfering with the TN/TP ratio. Thus, in the context of climate change and the eutrophication processes to which these reservoirs are subjected, modeling the responses of Chl-a concentrations to nutrients and hydroclimatic factors is crucial for developing water quality management strategies, especially specific nutrient reduction strategies for each water body. The generated relationships can also be combined with hydrological models in order to predict the impacts of extreme events and climate change on Chl-a concentrations (Raulino et al. 2021; Rabelo et al. 2021, 2022).

**Fig. 5** Most unfavorable (scenario A) and favorable (scenario B) results regarding the concentration of chlorophyll-a estimated through the empirical equations for the strategic reservoirs Castanhão/MJ and Orós/AJ



## Conclusions

The main purpose of this study was to use simple empirical methods to build a model to predict Chl-a based on hydroclimatic and nutrient data from multiple tropical reservoirs, and to analyze the relationships between the input variables and Chl-a. Spatiotemporal analysis showed that seasonal dynamics induced significant changes in the water quality so that the concentrations of Chl-a showed an increasing trend with the reduction of the accumulation volume and the increase of TN and TP. The analysis of the importance of input variables in predicting Chl-a indicated that TN better explained the variability of Chl-a in 58% of reservoirs and was superior to TP in 73% of cases, indicating that TN is the most important predictor.

The developed models were able to reproduce the temporal dynamics of Chl-a in the reservoirs. However, the input variables had different influences on the model's outcome. For most reservoirs, nutrient increases promoted an increase in the levels of Chl-a. The cases in which the increase in nutrients is unfavorable to the reduction of Chl-a can be associated with limiting nutrient shifting and the limitation of phytoplankton growth due to light deficiency in abiotic turbidity conditions promoted by the practice of fish farming in these reservoirs. Similarly, although volume generally showed an inverse relationship with Chl-a, it had the opposite effect for some reservoir models. Likewise, the increase in Chl-a concentration is dictated in 49% of the reservoirs by the increase and in 51% by the reduction of daily precipitation, indicating that each reservoir has a different response concerning nutrient dilution or enrichment effects associated with the increase in inflow, which is a response of precipitation in the basin.

The simulations of input scenarios of class changes showed that regardless of the phosphorus concentrations in the two strategic reservoirs, the Chl-a concentration classes became more critical in scenarios with high nitrogen loads. This pattern indicates that measures to individually control phosphorus production in reservoirs may not be sufficient to control eutrophication. In such cases, reservoir management techniques may be required to maintain the TN concentration in the water at acceptable levels. These results provide a reference for monitoring Chl-a fluctuations and understanding the mechanisms underlying nutrient concentrations in different reservoirs. By understanding the combined effect of nutrients and hydroclimatic variables on algae production in reservoirs, this study can provide valuable information for decision-making and planning strategies to control water quality in tropical reservoirs. The proposed relationships can

also be combined with hydrological models to predict the impacts of extreme events and climate change on Chl-a concentrations.

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**Data availability** Data available upon request.

## Declarations

**Ethics approval and consent to participate** Not applicable.

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**Competing interests** The authors declare no competing interests.

## References

- Alberto L, Mendonça R, Frischkorn H, Santiago MMF, Mendes Filho J (2004) Probing the relationship between surface waters and aquifers by 18O measurements on the top of the Araripe Plateau/NE Brazil. *Environ Geol* 46:295–302. <https://doi.org/10.1007/s00254-004-0975-6>
- Andrade EM, Ferreira KCD, Lopes FB, Araújo IC da S, Silva AGR da (2020) Balance of nitrogen and phosphorus in a reservoir in the tropical semi-arid region. *Rev Ciênc Agron* 51(1). <https://doi.org/10.5935/1806-6690.20200020>
- APHA (2005) Standard Methods for the Examination Water and Wastewater, twenty-first ed. APHA, Washington, p. 1083. American Public Health Association
- Aranha TRBT, Martinez J-M, Souza EP, Barros MUG, Martins ESPR (2022) Remote analysis of the chlorophyll-a concentration using Sentinel-2 MSI images in a semiarid environment in northeastern Brazil. *Water (Basel)* 14:451. <https://doi.org/10.3390/w14030451>
- Araújo JC, Bronstert A (2016) A method to assess hydrological drought in semi-arid environments and its application to the Jaguaribe River basin, Brazil. *Water Int* 41:213–230. <https://doi.org/10.1080/02508060.2015.1113077>
- Bachmann RW, Hoyer MV, Canfield DE (2003) Predicting the frequencies of high chlorophyll levels in Florida lakes from average chlorophyll or nutrient data. *Lake Reserv Manag* 19:229–241. <https://doi.org/10.1080/07438140309354088>
- Bai J, Yu Z, Yu L, Wang D, Guan Y, Liu X, Gu C, Cui B (2019) In-situ organic phosphorus mineralization in sediments in coastal wetlands with different flooding periods in the Yellow River

- Delta, China. *Sci Total Environ* 682:417–425. <https://doi.org/10.1016/j.scitotenv.2019.05.176>
- Bilgin A, Bayraktar HD (2021) Assessment of lake water quality using multivariate statistical techniques and chlorophyll-nutrient relationships: a case study of the Göksu Lake. *Arab J Geosci* 14:483. <https://doi.org/10.1007/s12517-021-06871-4>
- Bortoletto EC, Silva HA, Bonifácio CM, Tavares CRG (2015) Water quality monitoring of the Pirapó River watershed, Paraná, Brazil. *Braz J Biol* 75:148–157. <https://doi.org/10.1590/1519-6984.00313suppl>
- Brasil (2005) Resolução CONAMA N° 357 de 18 de Março de 2005. “Dispõe sobre a classificação dos corpos de água e diretrizes ambientais para o seu enquadramento, bem como estabelece as condições e padrões de lançamento de efluentes, e dá outras providências”. MMA Ministério do Meio Ambiente: 58–63. URL [https://www.icmbio.gov.br/cepsul/images/stories/legis\\_lacao/Resolucao/2005/res\\_conama\\_357\\_2005\\_classificacao\\_corpos\\_agua\\_rtfcd\\_a\\_altrd\\_res\\_393\\_2007\\_397\\_2008\\_410\\_2009\\_430\\_2011.pdf](https://www.icmbio.gov.br/cepsul/images/stories/legis_lacao/Resolucao/2005/res_conama_357_2005_classificacao_corpos_agua_rtfcd_a_altrd_res_393_2007_397_2008_410_2009_430_2011.pdf)
- Campos JNB (2011) Águas superficiais no semiárido brasileiro: desafios ao atendimento aos usos múltiplos. Recursos hídricos em regiões áridas e semiárida. Instituto Nacional do Semiárido - INSA, pp 249–268
- Canfield DE (1983) Prediction of chlorophyll a concentrations in Florida lakes: the importance of phosphorus and nitrogen. *J Am Water Resour Assoc* 19:255–262. <https://doi.org/10.1111/j.1752-1688.1983.tb05323.x>
- Carneiro FM, Nabout JC, Vieira LCG, Roland F, Bini LM (2014) Determinants of chlorophyll-a concentration in tropical reservoirs. *Hydrobiologia* 740:89–99. <https://doi.org/10.1007/s10750-014-1940-3>
- Carvalho TMN, Lima Neto IE, Souza Filho FA (2022) Uncovering the influence of hydrological and climate variables in chlorophyll-A concentration in tropical reservoirs with machine learning. *Environ Sci Pollut Res*. <https://doi.org/10.1007/s11356-022-21168-z>
- Cavalcante H, Araújo F, Becker V (2018) Phosphorus dynamics in the water of tropical semiarid reservoirs in a prolonged drought period. *Acta Limnologia Brasiliensia* 30: e105. <https://doi.org/10.1590/s2179-975x1617>
- Cavalcante H, Araújo F, Becker V, Barbosa JEL (2021) Internal phosphorus loading potential of a semiarid reservoir: an experimental study. *Acta Limnol Bras* 33:e6. <https://doi.org/10.1590/s2179-975x10220>
- Ceará (2018) Matriz dos Usos Múltiplos dos Açudes. Fortaleza. <http://www.hidro.ce.gov.br/hidro-ce-zend/mi/midia/show/149>
- Ceará, 2021. Portal Hidrológico do Ceará [WWW Document]. <http://www.hidro.ce.gov.br/>
- Ceará (2022a) Calendário Chuvas do Estado do Ceará [WWW Document]. <http://www.funceme.br/app-calendario/diario/municipios/maxima/2022/10>
- Ceará (2022b) Planos de recursos hídricos das regiões hidrográficas do Ceará: diagnóstico da região hidrográfica da serra da Ibiapaba. Fortaleza. <https://portal.cogerh.com.br/plano-de-recursos-hidricos-por-bacias-hidrografica/>
- Chaves LCG, Lopes FB, Maia ARS, Meireles ACM, Andrade EM (2019) Water quality and anthropogenic impact in the watersheds of service reservoirs in the Brazilian semi-arid region. *Rev Ciênc Agron* 50:223–233. <https://doi.org/10.5935/1806-6690.20190026>
- Chen D, Hu M, Guo Y, Dahlgren RA (2015) Influence of legacy phosphorus, land use, and climate change on anthropogenic phosphorus inputs and riverine export dynamics. *Biogeochemistry* 123:99–116. <https://doi.org/10.1007/s10533-014-0055-2>
- Chicco D, Warrens MJ, Jurman G (2021) The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Comput Sci* 7:1–24. <https://doi.org/10.7717/PEERJ-CS.623>
- Chusnah WN, Chu H-J (2022) Estimating chlorophyll-a concentrations in tropical reservoirs from band-ratio machine learning models. *Remote Sens Appl* 25:100678. <https://doi.org/10.1016/j.rsase.2021.100678>
- Coffey R, Paul MJ, Stamp J, Hamilton A, Johnson T (2019) A review of water quality responses to air temperature and precipitation changes 2: nutrients, algal blooms, sediment, pathogens. *JAWRA J Am Water Resour Assoc* 55:844–868. <https://doi.org/10.1111/1752-1688.12711>
- Cortez HS, Lima GP, Sakamoto MS (2017) A seca 2010–2016 e as medidas do Estado do Ceará para mitigar seus efeitos. *Revista Parcerias Estratégicas* 3(22):83–118
- Cruz MAS, Gonçalves AA, Aragão R, Amorim JRA, Mota PVM, Srinivasan VS, Garcia CAB, Figueiredo EE (2019a) Spatial and seasonal variability of the water quality characteristics of a river in Northeast Brazil. *Environ Earth Sci* 78:68. <https://doi.org/10.1007/s12665-019-8087-5>
- Cruz PS, Viana LG, Ceballos BSO (2019b) Reservatórios tropicais: Eutrofização e florações cianobactérias. In: *Semiárido Brasileiro*. Poisson, Belo Horizonte, pp. 33–42
- Cruz-Ramírez AK, Salcedo MÁ, Sánchez AJ, Barba Macías E, Mendoza Palacios JD (2019) Relationship among physicochemical conditions, chlorophyll-a concentration, and water level in a tropical river–floodplain system. *Int J Environ Sci Technol* 16:3869–3876. <https://doi.org/10.1007/s13762-018-2127-7>
- Dillon PJ, Rigler FH (1974) The phosphorus-chlorophyll relationship in lakes 1,2. *Limnol Oceanogr* 19:767–773. <https://doi.org/10.4319/lo.1974.19.5.0767>
- Ding S, Chen M, Gong M, Fan X, Qin B, Xu H, Gao SS, Jin Z, Tsang DCW, Zhang C (2018) Internal phosphorus loading from sediments causes seasonal nitrogen limitation for harmful algal blooms. *Sci Total Environ* 625:872–884. <https://doi.org/10.1016/j.scitotenv.2017.12.348>
- Feng W, Yang F, Zhang C, Liu J, Song F, Chen H, Zhu Y, Liu S, Giesy JP (2020) Composition characterization and biotransformation of dissolved, particulate and algae organic phosphorus in eutrophic lakes. *Environ Pollut* 265:114838. <https://doi.org/10.1016/j.envpol.2020.114838>
- Figueiredo ADV, Becker V (2018) Influence of extreme hydrological events in the quality of water reservoirs in the semi-arid tropical region. *RBRH* 23:e53. <https://doi.org/10.1590/2318-0331.231820180088>
- Franklin JB, Sathish T, Vinithkumar NV, Kirubakaran R (2020) A novel approach to predict chlorophyll-a in coastal-marine ecosystems using multiple linear regression and principal component scores. *Mar Pollut Bull* 152:110902. <https://doi.org/10.1016/j.marpolbul.2020.110902>
- Freire LL, Costa AC, Lima Neto IE (2021) Spatio-temporal patterns of river water quality in the semiarid northeastern Brazil. *Water Air Soil Pollut* 232:452. <https://doi.org/10.1007/s11270-021-05406-7>
- Freire LL, Costa AC, Lima Neto IE (2022) Effects of rainfall and land use on river nutrient dynamics in the Brazilian semiarid region. *Environ Monit Assess* 195:652. <https://doi.org/10.1007/s10661-023-11281-y>
- Geraldes AM, Boavida M (2005) Seasonal water level fluctuations: Implications for reservoir limnology and management. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use* 10:59–69. <https://doi.org/10.1111/j.1440-1770.2005.00257.x>
- Gidudu A, Letaru L, Kulabako RN (2021) Empirical modeling of chlorophyll a from MODIS satellite imagery for trophic status monitoring of Lake Victoria in East Africa. *J Great Lakes Res* 47:1209–1218. <https://doi.org/10.1016/j.jglr.2021.05.005>
- González Sagrario MA, Jeppesen E, Gomà J, Søndergaard M, Jensen JP, Lauridsen T, Landkildehus F (2005) Does high nitrogen

- loading prevent clear-water conditions in shallow lakes at moderately high phosphorus concentrations? *Freshw Biol* 50:27–41. <https://doi.org/10.1111/j.1365-2427.2004.01290.x>
- HaRa J, Atique U, An K-G (2020) Multiyear links between water chemistry, algal chlorophyll, drought-flood regime, and nutrient enrichment in a morphologically complex reservoir. *Int J Environ Res Public Health* 17:3139. <https://doi.org/10.3390/ijerph17093139>
- Harris TD, Wilhelm FM, Graham JL, Loftin KA (2014) Experimental manipulation of TN: TP ratios suppress cyanobacterial biovolume and microcystin concentration in large-scale in situ mesocosms. *Lake Reserv Manag* 30:72–83. <https://doi.org/10.1080/10402381.2013.876131>
- Hecht JS, Zia A, Clemins PJ, Schroth AW, Winter JM, Oikonomou PD, Rizzo DM (2022) Modeling the sensitivity of cyanobacteria blooms to plausible changes in precipitation and air temperature variability. *Sci Total Environ* 812:151586. <https://doi.org/10.1016/j.scitotenv.2021.151586>
- Hennemann MC, Petrucio MM (2016) High chlorophyll a concentration in a low nutrient context: discussions in a subtropical lake dominated by Cyanobacteria. *J Limnol.* <https://doi.org/10.4081/jlimnol.2016.1347>
- Ho JC, Michalak AM (2020) Exploring temperature and precipitation impacts on harmful algal blooms across continental U.S. lakes. *Limnol Oceanogr* 65:992–1009. <https://doi.org/10.1002/lno.11365>
- Huang H, Winter JM, Osterberg EC, Hanrahan J, Bruyère CL, Clemins P, Beckage B (2020) Simulating precipitation and temperature in the Lake Champlain basin using a regional climate model: limitations and uncertainties. *Clim Dyn* 54:69–84. <https://doi.org/10.1007/s00382-019-04987-8>
- Jargal N, Atique U, Mamun M, An K-G (2021) Seasonal and long-term connections between trophic status, sestonic chlorophyll, nutrients, organic matter, and monsoon rainfall in a multipurpose reservoir. *Water (Basel)* 13:1720. <https://doi.org/10.3390/w13131720>
- Jones JR, Bachmann RW (1976) Prediction of phosphorus and chlorophyll levels in lakes. *J Water Pollut Control Fed* 48:2176–2182
- Kayastha P, Dzialowski AR, Stoodley SH, Wagner KL, Mansaray AS (2022) Effect of time window on satellite and ground-based data for estimating chlorophyll-a in reservoirs. *Remote Sens (Basel)* 14:846. <https://doi.org/10.3390/rs14040846>
- Kim K-M, Ahn J-H (2022) Machine learning predictions of chlorophyll-a in the Han river basin, Korea. *J Environ Manage* 318:115636. <https://doi.org/10.1016/j.jenvman.2022.115636>
- Kim HG, Hong S, Chon T-S, Joo G-J (2021) Spatial patterning of chlorophyll a and water-quality measurements for determining environmental thresholds for local eutrophication in the Nakdong River basin. *Environ Pollut* 268:115701. <https://doi.org/10.1016/j.envpol.2020.115701>
- Kim JY, Atique U, Mamun M, An K-G (2021b) Long-term interannual and seasonal links between the nutrient regime, sestonic chlorophyll and dominant bluegreen algae under the varying intensity of monsoon precipitation in a drinking water reservoir. *Int J Environ Res Public Health* 18:2871. <https://doi.org/10.3390/ijerph18062871>
- Lewandowski J, Meinikmann K, Nützmann G, Rosenberry DO (2015) Groundwater - the disregarded component in lake water and nutrient budgets. Part 2: effects of groundwater on nutrients. *Hydrol Process* 29:2922–2955. <https://doi.org/10.1002/hyp.10384>
- Li N, Wang J, Yin W, Jia H, Xu J, Hao R, Zhong Z, Shi Z (2021a) Linking water environmental factors and the local watershed landscape to the chlorophyll a concentration in reservoir bays. *Sci Total Environ* 758:143617. <https://doi.org/10.1016/j.scitotenv.2020.143617>
- Li T, Zhang Y, He B, Yang B, Huang Q (2021b) Periodically hydrologic alterations decouple the relationships between physicochemical variables and chlorophyll-a in a dam-induced urban lake. *J Environ Sci (China)* 99:187–195. <https://doi.org/10.1016/j.jes.2020.06.014>
- Liao Z, Zang N, Wang X, Li C, Liu Q (2021) Machine learning-based prediction of chlorophyll-a variations in receiving reservoir of world's largest water transfer project—a case study in the Miyun Reservoir, North China. *Water (Basel)* 13:2406. <https://doi.org/10.3390/w13172406>
- Lima Neto IE, Wiegand MC, Araújo JC (2011) Sediment redistribution due to a dense reservoir network in a large semi-arid Brazilian basin. *Hydrol Sci J* 56:319–333. <https://doi.org/10.1080/02626667.2011.553616>
- Lima Neto IE, Medeiros PHA, Costa AC, Wiegand MC, Barros ARM, Barros MUG (2022) Assessment of phosphorus loading dynamics in a tropical reservoir with high seasonal water level changes. *Sci Total Environ* 815:152875. <https://doi.org/10.1016/j.scitotenv.2021.152875>
- Lira CCS, Medeiros PHA, Lima Neto IE (2020) Modelling the impact of sediment management on the trophic state of a tropical reservoir with high water storage variations. *An Acad Bras Cienc* 92:e20181169. <https://doi.org/10.1590/0001-3765202020181169>
- Liu J, Zhang Y, Yuan D, Song X (2015) Empirical estimation of total nitrogen and total phosphorus concentration of urban water bodies in china using high resolution IKONOS multispectral imagery. *Water (Switzerland)* 7:6551–6573. <https://doi.org/10.3390/w7116551>
- Liu X, Teubner K, Chen Y (2016) Water quality characteristics of Poyang Lake, China, in response to changes in the water level. *Hydrol Res* 47:238–248. <https://doi.org/10.2166/nh.2016.209>
- Lopes FB, Barbosa CCF, Novo EMLM, Carvalho LAS, Andrade EM, Teixeira A dos S (2021) Modelling chlorophyll-a concentrations in a continental aquatic ecosystem of the Brazilian semi-arid region based on remote sensing. *Rev Ciênc Agron* 52(2):e20207210. <https://doi.org/10.5935/1806-6690.20210028>
- Lu F, Chen Z, Liu W, Shao H (2016) Modeling chlorophyll-a concentrations using an artificial neural network for precisely ecorestoring lake basin. *Ecol Eng* 95:422–429. <https://doi.org/10.1016/j.ecoleng.2016.06.072>
- Lu L, Gong Z, Liang Y, Liang S (2022) Retrieval of chlorophyll-a concentrations of class ii water bodies of inland lakes and reservoirs based on ZY1-02D satellite hyperspectral data. *Remote Sens (Basel)* 14:1842. <https://doi.org/10.3390/rs14081842>
- Luo W, Zhu S, Wu S, Dai J (2019) Comparing artificial intelligence techniques for chlorophyll-a prediction in US lakes. *Environ Sci Pollut Res* 26:30524–30532. <https://doi.org/10.1007/s11356-019-06360-y>
- Machado CJF, Santiago MMF, Mendonça LAR, Frishkorn H, Mendes Filho J (2004) Hidrogeoquímica como indicador de interconexão entre aquíferos na chapada do araripe utilizando o aplicativo PHREEQC. *Águas Subterrâneas* 18(1). <https://doi.org/10.14295/ras.v18i1.1340>
- Malveira VTC, Araújo JC, Güntner A (2012) Hydrological impact of a high-density reservoir network in semiarid northeastern Brazil. *J Hydrol Eng* 17:109–117. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000404](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000404)
- Mamede GL, Guentner A, Medeiros PHA, Araújo JC, Bronstert A (2018) Modeling the effect of multiple reservoirs on water and sediment dynamics in a semiarid catchment in Brazil. *J Hydrol Eng* 23:5018020. [https://doi.org/10.1061/\(asce\)he.1943-5584.0001701](https://doi.org/10.1061/(asce)he.1943-5584.0001701)



- Mamun M, An KG (2017) Major nutrients and chlorophyll dynamics in Korean agricultural reservoirs along with an analysis of trophic state index deviation. *J Asia Pac Biodivers* 10:183–191. <https://doi.org/10.1016/j.japb.2017.04.001>
- Mamun M, Atique U, An K-G (2021a) Assessment of water quality based on trophic status and nutrients-chlorophyll empirical models of different elevation reservoirs. *Water (Basel)* 13:3640. <https://doi.org/10.3390/w13243640>
- Mamun M, Ferdous J, An K-G (2021b) Empirical estimation of nutrient, organic matter and algal chlorophyll in a drinking water reservoir using Landsat 5 TM data. *Remote Sens (Basel)* 13:2256. <https://doi.org/10.3390/rs13122256>
- McCrackin ML, Jones HP, Jones PC, Moreno-Mateos D (2017) Recovery of lakes and coastal marine ecosystems from eutrophication: a global meta-analysis. *Limnol Oceanogr* 62:507–518. <https://doi.org/10.1002/LNO.10441>
- Mesquita JBF, Lima Neto IE, Raabe A, Araújo JC (2020) The influence of hydroclimatic conditions and water quality on evaporation rates of a tropical lake. *J Hydrol (Amst)* 590:125456. <https://doi.org/10.1016/j.jhydrol.2020.125456>
- Michalak AM, Anderson EJ, Beletsky D, Boland S, Bosch NS, Bridgeman TB, Chaffin JD, Cho K, Confesor R, Daloğlu I, DePinto JV, Evans MA, Fahnenstiel GL, He L, Ho JC, Jenkins L, Johengen TH, Kuo KC, LaPorte E, Liu X, McWilliams MR, Moore MR, Posselt DJ, Richards RP, Scavia D, Steiner AL, Verhamme E, Wright DM, Zagorski MA (2013) Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions. *Proc Natl Acad Sci* 110(6448):6452. <https://doi.org/10.1073/pnas.1216006110>
- Moriyasi DN, Gitau MW, Pai N, Daggupati P (2015) Hydrologic and water quality models: performance measures and evaluation criteria. *Trans ASABE* 58:1763–1785. <https://doi.org/10.13031/trans.58.10715>
- Moura DS, Lima Neto IE, Clemente A, Oliveira S, Pestana CJ, Aparecida Melo M, Capelo-Neto J (2020) Modeling phosphorus exchange between bottom sediment and water in tropical semi-arid reservoirs. *Chemosphere* 246:125686. <https://doi.org/10.1016/j.chemosphere.2019.125686>
- Namsaraev Z, Melnikova A, Komova A, Ivanov V, Rudenko A, Ivanov E (2020) Algal bloom occurrence and effects in Russia. *Water* 12(1):285. <https://doi.org/10.3390/w12010285>
- Padedda BM, Sechi N, Lai GG, Mariani MA, Pulina S, Sarria M, Satta CT, Virdis T, Buscarinu P, Lugliè A (2017) Consequences of eutrophication in the management of water resources in Mediterranean reservoirs: a case study of Lake Cedrino (Sardinia, Italy). *Glob Ecol Conserv* 12:21–35. <https://doi.org/10.1016/J.GECCO.2017.08.004>
- Paerl HW, Scott JT, McCarthy MJ, Newell SE, Gardner WS, Havens KE, Hoffman DK, Wilhelm SW, Wurtsbaugh WA (2016) It takes two to tango: when and where dual nutrient (N & P) reductions are needed to protect lakes and downstream ecosystems. *Environ Sci Technol* 50:10805–10813. <https://doi.org/10.1021/acs.est.6b02575>
- Park Y, Cho KH, Park J, Cha SM, Kim JH (2015) Development of early-warning protocol for predicting chlorophyll-a concentration using machine learning models in freshwater and estuarine reservoirs, Korea. *Sci Total Environ* 502:31–41. <https://doi.org/10.1016/j.scitotenv.2014.09.005>
- Pontes Filho JD, Souza Filho FA, Martins ESPR, Studart TMC (2020) Copula-based multivariate frequency analysis of the 2012–2018 drought in northeast Brazil. *Water (Basel)* 12:834. <https://doi.org/10.3390/w12030834>
- Prairie YT, Duarte CM, Kalff J (1989) Unifying nutrient-chlorophyll relationships in lakes. *Can J Fish Aquat Sci* 46:1176–1182. <https://doi.org/10.1139/f89-153>
- Pridmore RD, Vant WN, Rutherford JC (1985) Chlorophyll-nutrient relationships in North Island lakes (New Zealand). *Hydrobiologia* 121:181–189. <https://doi.org/10.1007/BF00008722>
- Rabelo UP, Dietrich J, Costa AC, Simshäuser MN, Scholz FE, Nguyen VT, Lima Neto IE (2021) Representing a dense network of ponds and reservoirs in a semi-distributed dryland catchment model. *J Hydrol* 603:127103. <https://doi.org/10.1016/j.jhydrol.2021.127103>
- Rabelo UP, Costa AC, Dietrich J, Fallah-Mehdipour E, van Oel P, Lima Neto IE (2022) Impact of dense networks of reservoirs on streamflows at dryland catchments. *Sustainability* 14:14117. <https://doi.org/10.3390/su142114117>
- Raulino JBS, Silveira CS, Lima Neto IE (2021) Assessment of climate change impacts on hydrology and water quality of large semi-arid reservoirs in Brazil. *Hydrol Sci J* 66:1321–1336. <https://doi.org/10.1080/02626667.2021.1933491>
- Reynolds CS (1992) Eutrophication and the management of planktonic algae: what Vollenweider couldn't tell us, vol 3. FBA Special Publications, pp 4–29. <http://hdl.handle.net/1834/22792>
- Rocha MJD, Lima Neto IE (2020) Relação entre fósforo total e vazão afluente nos principais reservatórios rurais do estado do Ceará no semiárido brasileiro. *Revista AIDIS Ingeniería y Ciencias Ambientales. Investigación, desarrollo y práctica* 13:715
- Rocha MJD, Lima Neto IE (2021) Modeling flow-related phosphorus inputs to tropical semi-arid reservoirs. *J Environ Manage* 295:113123. <https://doi.org/10.1016/j.jenvman.2021.113123>
- Rocha MJD, Lima Neto IE (2021b) Phosphorus mass balance and input load estimation from the wet and dry periods in tropical semi-arid reservoirs. *Environ Sci Pollut Res* 29:10027–10046. <https://doi.org/10.1007/s11356-021-16251-w>
- Rocha MJD, Lima Neto IE (2022) Internal phosphorus loading and its driving factors in the dry period of Brazilian semi-arid reservoirs. *J Environ Manage* 312:114983. <https://doi.org/10.1016/j.jenvman.2022.114983>
- Rocha SMG, Rocha MJ, Araújo GM, Becker H, Lima Neto IE (2022) Seasonal and interannual variability of residence time and total phosphorus in a small hypereutrophic lake in the Brazilian north-east. *Water SA* 48:278–285. <https://doi.org/10.17159/wsa/2022.v48.i3.3893>
- Rocha SMG, Mesquita JBF, Lima Neto IE (2020) Análise e modelagem das relações entre nutrientes e fitoplâncton em reservatórios do Ceará. *Revista Brasileira Ciências Ambientais (Online)* 134–147. <https://doi.org/10.5327/z2176-947820190536>
- Rotta L, Alcântara E, Park E, Bernardo N, Watanabe F (2021) A single semi-analytical algorithm to retrieve chlorophyll-a concentration in oligo-to-hypereutrophic waters of a tropical reservoir cascade. *Ecol Indic* 120:106913. <https://doi.org/10.1016/j.ecolind.2020.106913>
- Schindler DW (2006) Recent advances in the understanding and management of eutrophication. *Limnol Oceanogr* 51(1, part 2):56–363. [https://doi.org/10.4319/lo.2006.51.1\\_part\\_2.0356](https://doi.org/10.4319/lo.2006.51.1_part_2.0356)
- Schönbrunner IM, Preiner S, Hein T (2012) Impact of drying and re-flooding of sediment on phosphorus dynamics of river-floodplain systems. *Sci Total Environ* 432:329–337. <https://doi.org/10.1016/j.scitotenv.2012.06.025>
- Sinha E, Michalak AM, Balaji V (2017) Eutrophication will increase during the 21st century as a result of precipitation changes. *Science* 1979(357):405–408. <https://doi.org/10.1126/science.aan2409>
- Smith VH (1983) Low nitrogen to phosphorus ratios favor dominance by blue-green algae in lake phytoplankton. *Science* 1979(221):669–671. <https://doi.org/10.1126/science.221.4611.669>
- Stefanidis K, Varlas G, Vourka A, Papadopoulos A, Dimitriou E (2021) Delineating the relative contribution of climate related variables to chlorophyll-a and phytoplankton biomass in lakes using the

- ERA5-Land climate reanalysis data. *Water Res* 196:117053. <https://doi.org/10.1016/j.watres.2021.117053>
- Stepanova IE (2021) Analysis of the correlation between the phytoplankton development level, assessed by chlorophyll a, and nutrient concentrations in Rybinsk Reservoir. *Biol Bull* 48:193–198. <https://doi.org/10.1134/S1062359021020114>
- Tang Q, Peng L, Yang Y, Lin Q, Qian SS, Han B-P (2019) Total phosphorus-precipitation and chlorophyll a-phosphorus relationships of lakes and reservoirs mediated by soil iron at regional scale. *Water Res* 154:136–143. <https://doi.org/10.1016/j.watres.2019.01.038>
- Thi Hoang Yen T, Thai TT, van Tu N, Xuan Quang N, Thanh Luu P (2021) Environmental factors influencing chlorophyll-a concentration in Tri An Reservoir, Vietnam. *VNU Journal of Science: Earth and Environmental Sciences* 37(2). <https://doi.org/10.25073/2588-1094/vnuess.4535>
- Ventura DLT, Martinez JM, Attayde JL, Martins ESPR, Brandini N, Moreira LS (2022) Long-term series of chlorophyll-a concentration in Brazilian semiarid lakes from Modis imagery. *Water (Switzerland)* 14:400. <https://doi.org/10.3390/w14030400>
- Vollenweider RA (1968) Scientific fundamentals of the eutrophication of lakes and flowing waters, with particular reference to nitrogen and phosphorus as factors in eutrophication. *Limnol Oceanogr* 15:1. <https://doi.org/10.4319/lo.1970.15.1.0169>
- Wang Z, Wang J, Tan L (2014) Variation in photosynthetic activity of phytoplankton during the spring algal blooms in the adjacent area of Changjiang River estuary. *Ecol Indic* 45:465–473. <https://doi.org/10.1016/j.ecolind.2014.05.010>
- Wang J, Chen J, Ding S, Guo J, Christopher D, Dai Z, Yang H (2016) Effects of seasonal hypoxia on the release of phosphorus from sediments in deep-water ecosystem: A case study in Hongfeng Reservoir, Southwest China. *Environ Pollut* 219:858–865. <https://doi.org/10.1016/j.envpol.2016.08.013>
- Wang S, Gao Y, Jia J, Kun S, Lyu S, Li Z, Lu Y, Wen X (2021) Water level as the key controlling regulator associated with nutrient and gross primary productivity changes in a large floodplain-lake system (Lake Poyang), China. *J Hydrol (Amst)* 599:126414. <https://doi.org/10.1016/j.jhydrol.2021.126414>
- Wiegand MC, Nascimento ATPD, Costa AC, Lima Neto IE (2020) Avaliação nutriente limitante da produção algal em reservatórios do semiárido brasileiro. *Brazilian Journal of Environmental Sciences (Online)* 55:456–478. <https://doi.org/10.5327/Z2176-947820200681>
- Wiegand MC, Nascimento ATP, Costa AC, Lima Neto IE (2021) Trophic state changes of semi-arid reservoirs as a function of the hydro-climatic variability. *J Arid Environ* 184:104321. <https://doi.org/10.1016/j.jaridenv.2020.104321>
- Wilkinson GM, Walter JA, Buelo CD, Pace ML (2022) No evidence of widespread algal bloom intensification in hundreds of lakes. *Front Ecol Environ* 20:16–21. <https://doi.org/10.1002/fee.2421>
- 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, Kraemer BM, Lenters JD, Merchant CJ, O'Reilly CM, Sharma S (2020) Global lake responses to climate change. *Nat Rev Earth Environ* 1:388–403. <https://doi.org/10.1038/s43017-020-0067-5>
- Wu Z, Liu J, Huang J, Cai Y, Chen Y, Li K (2019) Do the key factors determining phytoplankton growth change with water level in China's largest freshwater lake? *Ecol Indic* 107:105675. <https://doi.org/10.1016/j.ecolind.2019.105675>
- Wu B, Dai S, Wen X, Qian C, Luo F, Xu J, Wang X, Li Y, Xi Y (2022) Chlorophyll-nutrient relationship changes with lake type, season and small-bodied zooplankton in a set of subtropical shallow lakes. *Ecol Indic* 135:108571. <https://doi.org/10.1016/j.ecolind.2022.108571>
- Xu T, Yang T, Xiong M (2020) Time scales of external loading and spatial heterogeneity in nutrients-chlorophyll a response: implication on eutrophication control in a large shallow lake. *Ecol Eng* 142:105636. <https://doi.org/10.1016/j.ecoleng.2019.105636>
- Xu T, Yang T, Zheng X, Li Z, Qin Y (2022) Growth limitation status and its role in interpreting chlorophyll a response in large and shallow lakes: a case study in Lake Okeechobee. *J Environ Manage* 302:114071. <https://doi.org/10.1016/j.jenvman.2021.114071>
- Yan Z, Han W, Peñuelas J, Sardans J, Elser JJ, Du E, Reich PB, Fang J (2016) Phosphorus accumulates faster than nitrogen globally in freshwater ecosystems under anthropogenic impacts. *Ecol Lett* 19:1237–1246. <https://doi.org/10.1111/ele.12658>
- Yu G, Zhang S, Qin W, Guo Y, Zhao R, Liu C, Wang C, Li D, Wang Y (2022) Effects of nitrogen and phosphorus on chlorophyll a in lakes of China: a meta-analysis. *Environ Res Lett* 17:074038. <https://doi.org/10.1088/1748-9326/ac7d64>
- Yuan LL, Jones JR (2020) Rethinking phosphorus-chlorophyll relationships in lakes. *Limnol Oceanogr* 9999:1–11. <https://doi.org/10.1002/lno.11422>
- Zeng Q, Liu Y, Zhao H, Sun M, Li X (2017) Comparison of models for predicting the changes in phytoplankton community composition in the receiving water system of an inter-basin water transfer project. *Environ Pollut* 223:676–684. <https://doi.org/10.1016/j.envpol.2017.02.001>
- Zhang L, Zhang L, Cen Y, Wang S, Zhang Y, Huang Y, Sultan M, Tong Q (2022) Prediction of total phosphorus concentration in macrophytic lakes using chlorophyll-sensitive bands: a case study of Lake Baiyangdian. *Remote Sens (Basel)* 14:3077. <https://doi.org/10.3390/rs14133077>
- Zou W, Zhu G, Xu H, Zhu M, Zhang Y, Qin B (2022) Temporal dependence of chlorophyll a–nutrient relationships in Lake Taihu: drivers and management implications. *J Environ Manage* 306:114476. <https://doi.org/10.1016/j.jenvman.2022.114476>

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