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Research article

Modeling the effect of climate change scenarios on water quality for tropical reservoirs

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ABSTRACT

Impact of natural phenomena and anthropogenic activities on water quality is closely related with temperature increase and global warming. In this study, the effects of climate change scenarios on water quality forecasts were assessed through correlations, prediction algorithms, and water quality index (WQI) for tropical reservoirs. The expected trends for different water quality parameters were estimated for the 2030–2100 period in association with temperature trends to estimate water quality using historical data from a dam in Mexico. The WQI scenarios were obtained using algorithms supported by global models of representative concentration pathways (RCPs) adopted by the Intergovernmental Panel on Climate Change (IPCC). The RPCs were used to estimate water and air temperature values and extrapolate future WQI values for the water reservoir. The proposed algorithms were validated using historical information collected from 2012 to 2019 and four temperature variation intervals from 3.2 to 5.4 °C (worst forecast) to 0.9–2.3 °C (best forecast) were used for each trajectory using 0.1 °C increases to obtain the trend for each WQI parameter. Variations in the concentration (±30, ±70, and +100) of parameters related to anthropogenic activity (e.g., total suspended solids, fecal coliforms, and chemical oxygen demand) were simulated to obtain water quality scenarios for future health diagnosis of the reservoir. The results projected in the RCP models showed increasing WQI variation for lower temperature values (best forecast WQI = 74; worst forecast WQI = 71). This study offers a novel approach that integrates multiparametric statistical and WQI to help decision making on sustainable water resources management for tropical reservoirs impacted by climate change.

1. Introduction

Water quality monitoring and diagnosing surface water bodies is useful to assess the impact caused either by natural phenomena and/or anthropogenic activities (Geng et al., 2021; Jia et al., 2019; Kumar et al., 2020; Quevedo-Castro et al., 2019). The use of hydroclimatological and water quality variables is required to better understand the effects of these stressors on ecosystems and the response of ecosystems to these effects (Korkanc et al., 2017; Muñoz-Nájera et al., 2020). The study of water bodies over time using physical, chemical, and microbiological parameters help to generate a broader overview of the status of and conditions in reservoirs (Vasistha and Ganguly, 2020; Bouaroudj et al., 2019), particularly when productive activities (e.g., industry, agriculture, and livestock) are the main point and diffuse pollution sources (Okyereh et al., 2019). As the availability of secure water sources decreases because of increased human activities, water resources management that accounts for the effects of global warming becomes critical (Yaghoubi et al., 2020).

The increase in surface water contamination observed in recent years highlights the need for tools that describe future trends and help with forecasting potential variations in water quality (Arab et al., 2018). Several studies (Rocha et al., 2019; Saber et al., 2020; Messina et al., 2020; Me et al., 2018) have suggested the higher regional temperatures and frequent/intense precipitation caused by climate change will increase the discharge of suspended solids and nutrient loading to water bodies (Imneisi and Aydın, 2016; De la Mora-Orozco et al., 2017).

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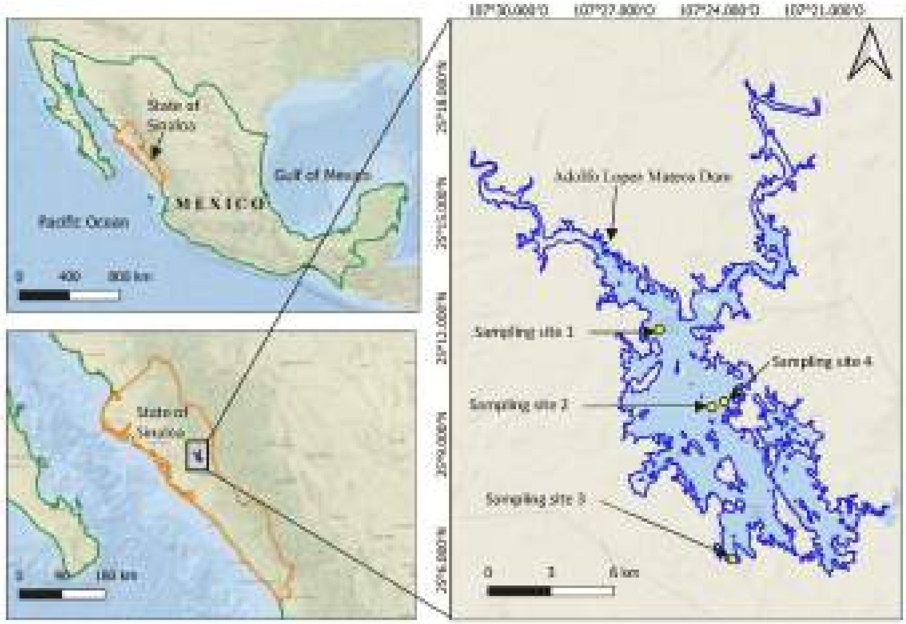

Fig. 1. ALMD and water quality sampling site's geographical location.

Therefore, studying trends and forecasting water quality variables is useful to predict behavior and provide valuable information for surface waterbodies management (Antunes et al., 2018). Water quality trends can be assessed through their relationship with climatological variables such as temperature (Xu et al., 2019; Li et al., 2020), considered playing a significant role on water quality (Rocha et al., 2019; Messina et al., 2020).

The need for new decision-making tools to predict water quality variations as a function of temperature changes as reports of water quality degradation increase (Loaiza et al., 2021). Some studies have evaluated water quality in tropical regions (Guillen et al., 2021; Tiyasha and Yaseen, 2021; Quang et al., 2019; Negri et al., 2020; Grbčić et al., 2021; Alias et al., 2021) considering climate change-related impacts, sediments and nutrients transport (Jayakody, 2014), hydrological cycle variation with temperature (Uriarte, 2011), demographic growth (Buytaert, 2012), and fecal contamination (Guo et al., 2021a, 2021b, 2021c). However, only few of these have reported predictive models that combine water quality and global climate change models, usually for water bodies located in colder environments (Me et al., 2018; Majedul et al., 2018). This lack of information is a significant knowledge gap highlighting the need for quantifying temperature variation impact on water quality for tropical regions (Simonetti et al., 2021; Shil et al., 2019; Mena-Rivera et al., 2017; Cude, 2001). Furthermore, application of such models is difficult when local conditions dynamics and natural/anthropogenic activities effects are considered for specific cases. Therefore, developing algorithms suitable for use in tropical environments is increasingly needed to predict the behavior of critical water quality parameters.

This study used different temperature intervals from global climate change models developed by the Intergovernmental Panel on Climate Change (IPCC) related to representative concentration pathway (RCP) to project trends and forecast water quality in a tropical climate using a reservoir in Mexico as a case study. The application of linear, parametric, and partial correlation tools as well as linear and multiple regression statistical techniques generated algorithms that were then used jointly with the proposed WQI to model water quality based on air and water temperature scenarios (Kothari et al., 2021). The study applied a proposed WQI as a statistical diagnostic tool for reservoirs located in tropical regions.

2. Materials and methods

2.1. Study area

This study used data from Adolfo Lopez Mateos Dam (ALMD) located in Sinaloa, Mexico, as the study area. The reservoir is a 113.40 km^2 tropical water body with 4034 hm^3 total capacity. The dam is located on the Humaya River watershed and operating since 1963, its main consumptive water uses are agricultural irrigation and pisciculture (Beltrán et al., 2015). Water and air temperature information in degrees centigrade (°C) (from 2012 to 2018) was collected in four sampling sites: P1 (−107.42565, 25.20128), P2 (−107.39996, 25.16813), P3 (−107.3889, 25.10275) and P4 (−107.39422, 25.1706) (see Fig. 1) from "El Varejonal" hydroclimatological station located nearby (CONAGUA, 2021).

2.2. Water quality parameters

For the four selected sampling sites described in section 2.1, a record was compiled of 26 physical, chemical, and microbiological water quality parameters: Chlorophyl a (Chl a), UV absorption (UVA), fecal coliform (FC), *Escherichia coli* (E.C.), total organic carbon (TOC), biochemical oxygen demand (BOD), chemical oxygen demand (COD), ammonia nitrogen (NH_3), nitrite (NO_2), nitrate (NO_3), organic nitrogen (ON), total nitrogen (TN), total Kjeldahl nitrogen (TNK), total phosphorus (TP), true color (TC), transparency (TRA), pH, electric conductivity (CON), total dissolved solid (TDS), dissolved oxygen (DO), total hardness (TH), orthophosphate (PO_4^{3-}), total suspended solid (TSS), turbidity (TUR), air temperature (AT), and water temperature (WT).

Water quality data was provided by the National Water Commission, Mexico (CONAGUA) from sampling campaigns carried out every six months (e.g., rainy, and dry seasons) from 2012 to 2018 at the four sampling sites described earlier (e.g., P1, P2, P3, and P4; see Fig. 1). Water quality parameters were estimated in agreement with the Standard Methods in an ISO accredited laboratory (APHA, 2017).

Water quality parameters were analyzed to obtain forecasts and future scenarios through direct and indirect correlations with water temperature (WT) and air temperature (AT) using the water quality index described elsewhere (Quevedo-Castro et al., 2018) for tropical reservoirs. Water quality parameters with a stronger linear correlation with WT and AT were identified using the Pearson correlation matrix and referred to as direct correlation parameters. The parameters that presented lower correlation with temperature were classified as indirect.

2.3. Correlation/association of parameters

Linear correlation matrices, nonparametric correlations, and partial correlations were constructed to evaluate the correlations/associations between 11 direct water quality parameters (FC, TSS, pH, DO, COD, ON, NH_3, NO_3, TP, PO_4^{3-} and Chl a) and temperature (WT and AT). The Pearson's correlation coefficient analysis was used to identify linear correlations between variables, whereas the Spearman rank correlation coefficient analysis was used for nonlinear associations forces of water quality variables. Spearman's rho is a non-parametric test to measure statistical dependence between the association between two variables. Partial correlations were used to identify the predictive strength among variables. The analysis was performed using Origin 9.1 software and graphics were created with RStudio. The range of Pearson, Spearman, and partial forces coefficients estimated was from −1 to +1 depending on the strength of the linear relationship between the variables, with 0 being the lowest correlation and ±1 being the highest correlation. A positive correlation (values from 0 to 1) means one variable increase when another increases. A negative correlation (−1 to 0) means one variable increase when another decreases. *P*-values below 0.05 were considered statistically significant with a 95.0% confidence level.

Once the direct and indirect parameters of the database were identified as a function of AT and WT, linear regression equations were constructed that included the direct and indirect variables as a function of the 11 parameters that make up the reservoir WQI. Simple regressions were used for cases of parameters with direct correlation to AT and WT. Regression analyses were used to estimated relationship between parameters and correlation/association with AT and WT. R-square and p-values were estimated to obtain an algorithm to predict water quality scenarios. Once the equations based on the AT and WT for each WQI variable were generated, calibration was carried out by substituting water quality and AT and WT variables from the database and comparing observed concentrations against predicted values.

2.4. Assessing the effect of global climate models in water quality

Future projections of water quality variations as a function of temperature were assessed using global temperature models adopted by the IPCC that include greenhouse gas concentrations (IPCC, 2018). The IPCC suggested four RCP trajectories according to CO_2 concentration (in parts per million, ppm) and temperature variation ranges used for predictive models over the next 100 years. RCP 8.5 ppm represents the highest temperature variation, whereas an RCP 2.6 ppm represents the lowest temperature variation (Salimi and Scholz, 2021; Guo et al., 2021a, 2021b, 2021c). The four RCP scenarios used in this study were: (a) 3.2–5.4 °C, RCP 8.5 ppm; (b) 2.0–3.7 °C, RCP 6 ppm; (c) 1.7–3.2 °C, RCP 4.5 ppm; and (d) 0.9–2.3 °C, RCP 2.6 ppm. Using these temperature variation intervals for proposed RCPs, projections of 11 water quality parameters for WQI were made. Simulations were performed for different RPCs based on WT and AT data. The trend of each water quality parameter was obtained as a function of the temperature variation for each projected year, which provided trends for each WQI parameter over the next 100 years.

2.5. Water quality index (WQI)

The WQI was calculated by using Eq. (1) reported previously (Quevedo-Castro et al., 2018).

$$WQI = \sum_{n=1}^{i} SI_n W_n \tag{1}$$

Table 1
Algorithms for predicting water quality scenarios in the ALMD.

Parameter	R-square	*P*-value	Algorithm
FC	88.03	0.004	$FC = 359.195 + 2.88109*TC + 2.14406*TSS + 66.6938*TUR - 7.37351*AT - 7.64135*WT$
TSS	89.84	0.0023	$TSS = -38.9027 + 60.8435*NO_{3-} + 238.327*TP + 2.84123*TUR - 0.506945*AT + 1.31766*WT$
pH	86.83	0.0013	$pH = 0.579286 + 0.00177434*COD + 0.269885*DO - 0.00759919*TH + 0.121751*AT + 0.0611671*WT$
DO	95.24	0.0005	$DO = 24.168 + 0.148525*AT - 0.655006*WT$
COD	88.17	0.0015	$COD = 113.201 + 4.60857*BOD + 32.4638*NH_3 + 65.1638*ON - 17.6245*pH + 0.0739097*TH + 1.94107*AT - 2.41093*WT$
ON	88.70	0.0033	$ON = -2.25199 + 0.0148534*AT + 0.0752578*WT$
NH_3	92.40	0.0014	$NH_3 = 0.483305 + 0.0104911*BOD - 0.0428745*ON - 0.00202097*TUR - 0.0151233*AT - 0.00107386*WT$
NO_3	99.99	0.0001	$NO_3 = -0.00898702 - 0.000187963*TOC + 0.883497*TN - 0.880494*TNK + 0.0000799737*TSS + 0.000461481*AT - 0.000422515*WT + 0.000249538*TC$
TP	93.41	0.0011	$TP = -0.0261668 - 0.00226919*AT + 0.0055921*WT$
PO_4^{3-}	90.91	0.0013	$PO_4 = 0.414488 + 0.00205479*NO_{3-} + 0.0778848*TP - 0.00927069*AT - 0.0024189*WT$
Chl a	74.78	0.0009	$Chl\,a = 110.301 - 3.22577*TNK - 1.15738*TRA - 1.31982*DO - 1.63807*AT - 1.05333*WT$

where *WQI* is the water quality index, SI_n is the quality function of every evaluated water quality parameter, W_n is the relative weight of every water quality parameter, and n is the number of water quality parameters that make up the system (Quevedo-Castro et al., 2018). Temperature variations and projections obtained for the different RCPs were used to simulate WQI calculations.

2.6. Development of the climate change model

Results of climate change models developed by the IPCC were applied to obtain water quality parameter values and water quality trends using Eq. (1). The algorithms were used to obtain the trend of each water quality parameter included in the WQI over time as function of temperature (AT and WT) variation projections. Once the four RCP trajectories (8.5, 6, 4.5 and 2.6 ppm) projection was calculated for 11 water quality parameters (FC, TSS, pH, DO, COD, ON, NH_3, NO_3, TP, PO_4^{3-} and Chl a) over time (e.g., 2030–2100), future behavior of each parameter based on AT and WT was simulated. Then, 11 WQI values were calculated (2030–2100) using projected values of every variable in relation to RCP trajectory. Simulated WQI values were obtained using the proposed algorithms to obtain corresponding values estimated for the same study period using RCP simulations (e.g., 2030 to 2100). After calculating WQI for the different scenarios, sensitivity of parameters attributed to anthropogenic contamination (FC, TSS and COD) was tested by varying projected results to simulate normal, pessimistic, and optimistic scenarios (±30%, ±70%, and +100%) to assess the effect of increased concentrations throughout the reservoir (Sidabutar et al., 2017; Aslan-Yılmaz et al., 2004).

Because only average water quality data was available and no point/diffuse contamination sources were identified, simulations of only three parameters attributed to anthropogenic contamination sources were attempted: fecal coliforms, total suspended solids, and chemical oxygen demand. In all these cases, specific increase, and decrease (±30%, ±70%, and +100%) of every anthropogenic-related parameter was

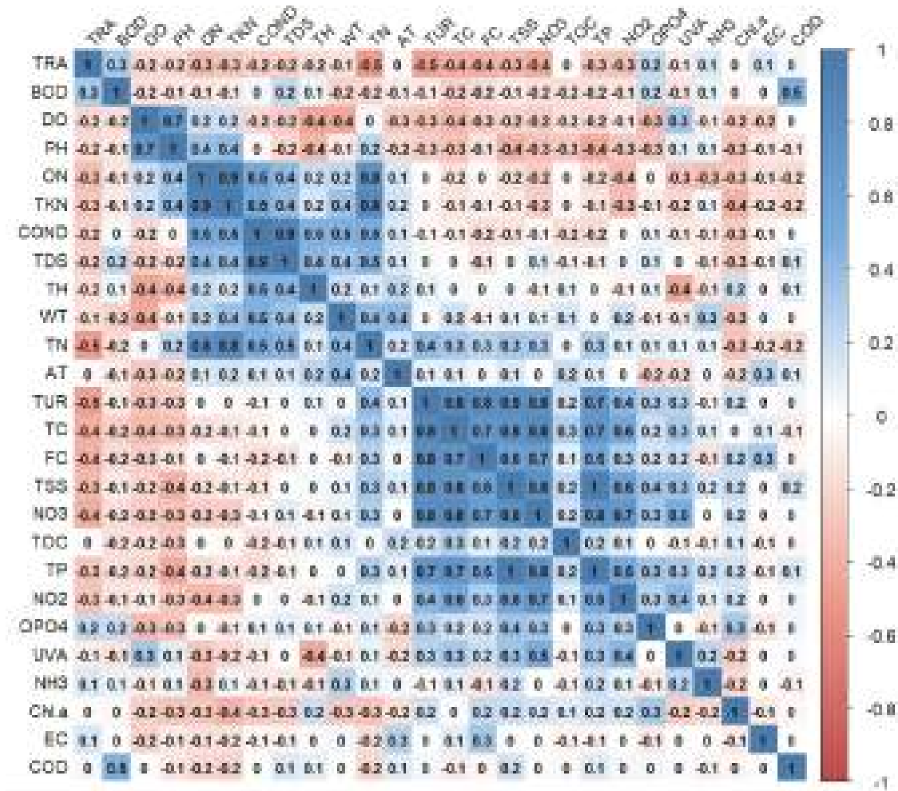

Fig. 2. Pearson correlation matrix of water quality parameters.

tested to evaluate the index sensitivity and predict effects of simulating changes by over the study period (e.g., 2030 to 2100).

2.7. Obtaining algorithms

Algorithms were created (Table 1) to model 11 WQI parameters (Quevedo-Castro et al., 2018) using statistical analysis to identify the R-squared and *p*-value for each model through linear and multiple regression. Regression analysis was performed on 26 water quality variables in the database to identify those that better represent the system through linear mathematical algorithms. Unlike the spatial and seasonal evaluations of the water quality of tropical water bodies by simulating hydroclimatological data (precipitation and temperature) found in the literature (Danladi Bello et al., 2017; Guo et al., 2021a, 2021b, 2021c; Fang et al., 2021; Jayakody et al., 2014; Delpla et al., 2009), the algorithm algorithms (Table 1) made it possible to estimate the quantitative impact of the temperature variation on each parameter compared to the Climate change projections from a proposed water quality index for tropical climates.

3. Results and discussion

3.1. Algorithm generation

Algorithms were generated and validated with available historical water quality data from the reservoir (2012–2018). Subsequently, WT and AT simulations and their effects on water quality were performed for all the resulting algorithms. The variation of water quality parameters according to the four RCP temperature intervals was analyzed, obtaining forecasts for changes in water quality for every parameter from 2018 to 2100.

The Pearson correlation coefficient was used with data from 26 water quality parameters (physical, chemical, and microbiological), including AT and WT from 2012 to 2018. Fig. 2 shows the correlations of each pair of 26 parameters. The color intensity shows the relationship between variables. Blue represents a positive correlation, whereas orange represents a negative correlation. DO, ON and TP turned out to be the three most directly related to correlation and association forces with respect to AT and WT. The remaining eight parameters were adjusted by direct (AT and WT) and indirect variables, according to data dispersion, using alternative variables to build each algorithm using the system; FC (TC, TSS and TUR), TSS (NO_3, TP and TUR), pH (COD, DO and TH), COD (BOD, NH_3, ON, pH and TH), NH_3 (BOD, ON and TUR), NO_3 (TOC, TN, NTK, TSS, TC), PO_4^{3-} (NO_3 and TP) and Chl a (TNK, TRA and DO) using multiple regression, R-square, and p-values to describe their correlation with AT and WT (Table 1).

AT and WT were found less influential than water quality parameters. However, AT and WT were related to some parameters because a warmer climate accelerates decomposition rate and nutrient release and causes eutrophication (Bouraï et al., 2020). Fecal coliforms showed strong positive correlation with TC (0.7), TSS (0.6), and TUR (0.8), probably because particulate matter caused by reservoir hydrodynamics, mineral solubility, and biological activity produced adsorption-desorption processes in the aquatic system (Sajjadi et al., 2017). Total suspended solids were with positive significant correlation with NO_3 (0.8), FC (0.6), PO_4^{3-} (0.4), and TUR (0.8) (Chapman, 2021) (Fig. 2). pH was found influencing TH (−0.4), TSS (−0.4) and oxygen-related parameters (e.g., DO (0.7) and COD (−0.1)) some of them related to gas solubility (Tripathi et al., 2014). DO, ON, and PO_4^{3-} were associated with AT (−0.3, 0.1, −0.2, respectively) and WT (−0.4, 0.2, −0.1, respectively). COD correlated with BOD (0.5), NH_3 (−0.1), ON (−0.2), pH (−0.1) and TH (0.1) probably because COD is susceptible to oxidation of organic and inorganic materials (Fig. 2). In the case of nitrogenous compounds, ON was correlated with pH (0.4), TKN (0.9), TN (0.8), and COND (0.5). Ammonia nitrogen was found influenced by ON (−0.3), whereas BOD presented low correlation with turbidity (−0.1). Nitrates showed interaction with TP (0.8), TN (0.3), TNK (−0.3), and TSS (0.8) probably because influence of nitrifying and denitrifying

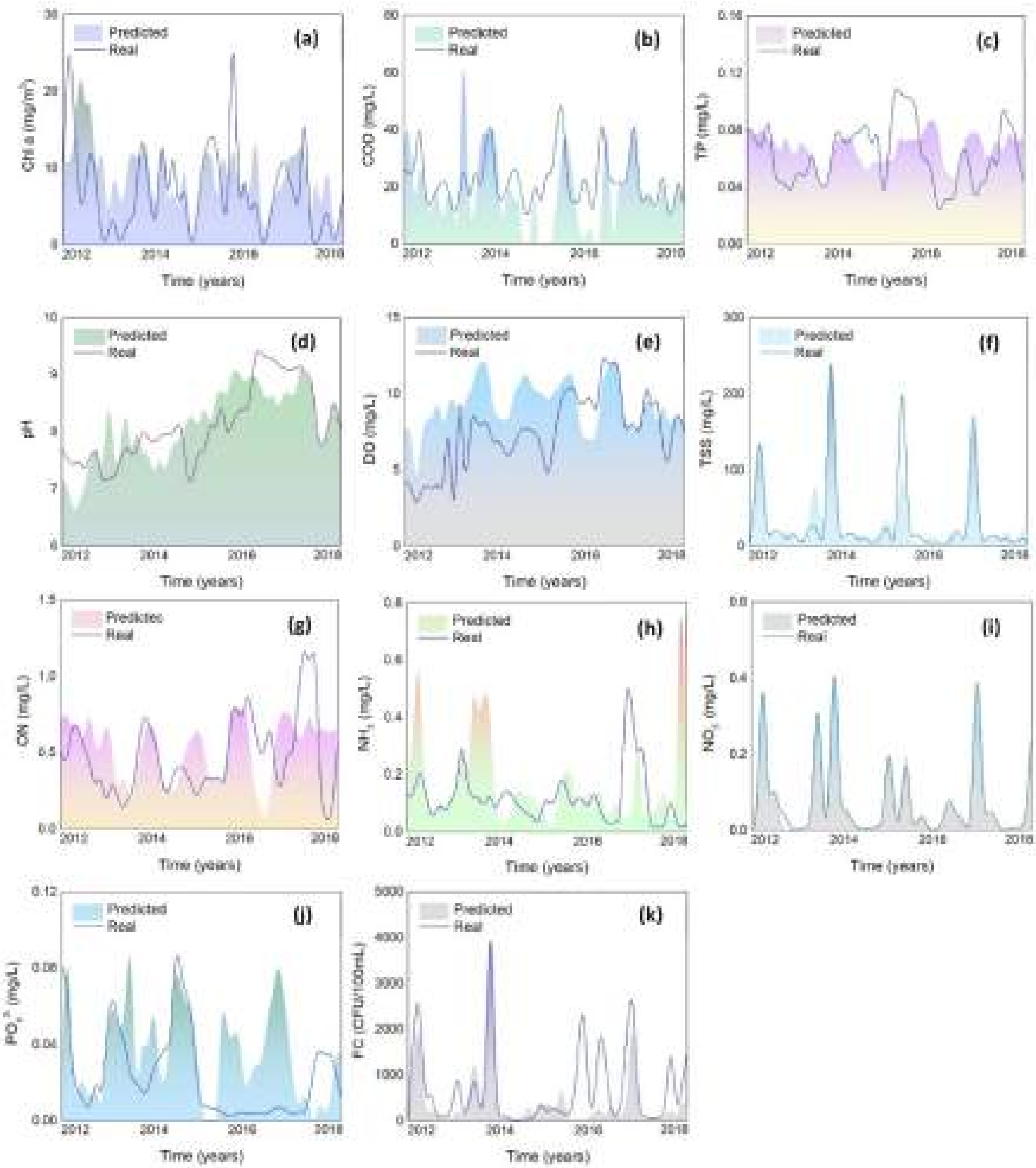

Fig. 3. Result calibration for the proposed algorithm.

bacteria (Chapman, 2021; Yang et al., 2021; Ni et al., 2018) (Fig. 2). Orthophosphate, an essential nutrient for living organisms and limiting nutrient for algae growth and primary productivity in eutrophication (Chapman, 2021), was found influenced by NO_3 (0.3) and TP (0.3). TP was correlated with TUR (0.7), NO_3 (0.8) and TC (0.7) (Berthe et al., 2018; Chapman, 2021) probably related with rock weathering and/or organic matter decomposition in the reservoir. Fecal coliforms showed strong correlation with TUR (0.8), TC (0.7), TP (0.5) and NO_3 (0.7) and Chl a was correlated with TNK (−0.4) and DO (−0.2) (Fig. 2) (Chapman, 2021) probably due to phytoplankton activity, toxic inhibition, and biological response to nutrients presence (Bai et al., 2022). The group of variables with the highest correlation corresponds to TUR, TC, FC, TSS and NO_3 and TP, PO_4^{3-}, NO_2, NTK and ON. Anthropogenic activities, mainly agriculture, were found impacting nutrient concentration, closely related to most of water quality parameters and influencing variation in water quality (Atique et al., 2019), COD, TN and TP were found significantly affected by agricultural runoff in agreement with other studies (Novotny, 2002; Saha et al., 2021).

3.2. Model calibration

Water quality behavior was modeled using 11 WQI parameters to calibrate predicting algorithms as a function of AT and WT. Fig. 3 shows the results for predicted and actual trends. A cubic spline interpolation was performed by dividing the input data into a set of fragments fitted to each segment with a cubic polynomial for the 11 parameters using the Origin Pro 8.5 software application. As shown in Fig. 3, predicted data match actual field data well for almost all parameters (particularly FC, NO_3, and TSS), in agreement with other studies (Salimi and Scholz, 2021) where future climate scenarios were simulated for the last 30

Table 2
Temperature fluctuations versus RCP.

RCP	variation (°C)	Forecast year	Air temperature (°C)	Water temperature (°C)
8.5 (3.2–5.4 °C)	3.2	2030	38.3	34.7
	3.3	2033	38.4	34.8
	3.4	2036	38.5	34.9
	3.5	2040	38.6	35.0
	3.6	2043	38.7	35.1
	3.7	2046	38.8	35.2
	3.8	2049	38.9	35.3
	3.9	2052	39.0	35.4
	4.0	2055	39.1	35.5
	4.1	2059	39.2	35.6
	4.2	2062	39.3	35.7
	4.3	2065	39.4	35.8
	4.4	2068	39.5	35.9
	4.5	2071	39.6	36.0
	4.6	2075	39.7	36.1
	4.7	2078	39.8	36.2
	4.8	2081	39.9	36.3
	4.9	2084	40.0	36.4
	5.0	2087	40.1	36.5
	5.1	2090	40.2	36.6
	5.2	2094	40.3	36.7
	5.3	2097	40.4	36.8
	5.4	2100	40.6	36.9
6 (2.0–3.7 °C)	2.0	2030	37.2	33.5
	2.1	2034	37.3	33.6
	2.2	2038	37.4	33.7
	2.3	2042	37.5	33.8
	2.4	2046	37.6	33.9
	2.5	2051	37.7	34.0
	2.6	2055	37.8	34.1
	2.7	2059	37.9	34.2
	2.8	2063	38.0	34.3
	2.9	2067	38.1	34.4
	3.0	2071	38.2	34.5
	3.1	2075	38.3	34.6
	3.2	2079	38.4	34.7
	3.3	2083	38.5	34.8
	3.4	2087	38.6	34.9
	3.5	2092	38.7	35.0
	3.6	2096	38.8	35.1
	3.7	2100	38.9	35.2
4.5 (1.7–3.2 °C)	1.7	2030	36.9	33.2
	1.8	2035	37.0	33.3
	1.9	2039	37.1	33.4
	2.0	2044	37.2	33.5
	2.1	2049	37.3	33.6
	2.2	2053	37.4	33.7
	2.3	2058	37.5	33.8
	2.4	2063	37.6	33.9
	2.5	2067	37.7	34.0
	2.6	2072	37.8	34.1
	2.7	2077	37.9	34.2
	2.8	2081	38.0	34.3
	2.9	2086	38.1	34.4
	3.0	2090	38.2	34.5
	3.1	2095	38.3	34.6
	3.2	2100	38.4	34.7
2.6 (0.9–2.3 °C)	0.9	2030	36.1	32.4
	1.0	2035	36.2	32.5
	1.1	2040	36.3	32.6
	1.2	2045	36.4	32.7
	1.3	2050	36.5	32.8
	1.4	2055	36.6	32.9
	1.5	2060	36.7	33.0
	1.6	2065	36.8	33.1
	1.7	2070	36.9	33.2
	1.8	2075	37.0	33.3
	1.9	2080	37.1	33.4
	2.0	2085	37.2	33.5
	2.1	2090	37.3	33.6
	2.2	2095	37.4	33.7
	2.3	2100	37.5	33.8

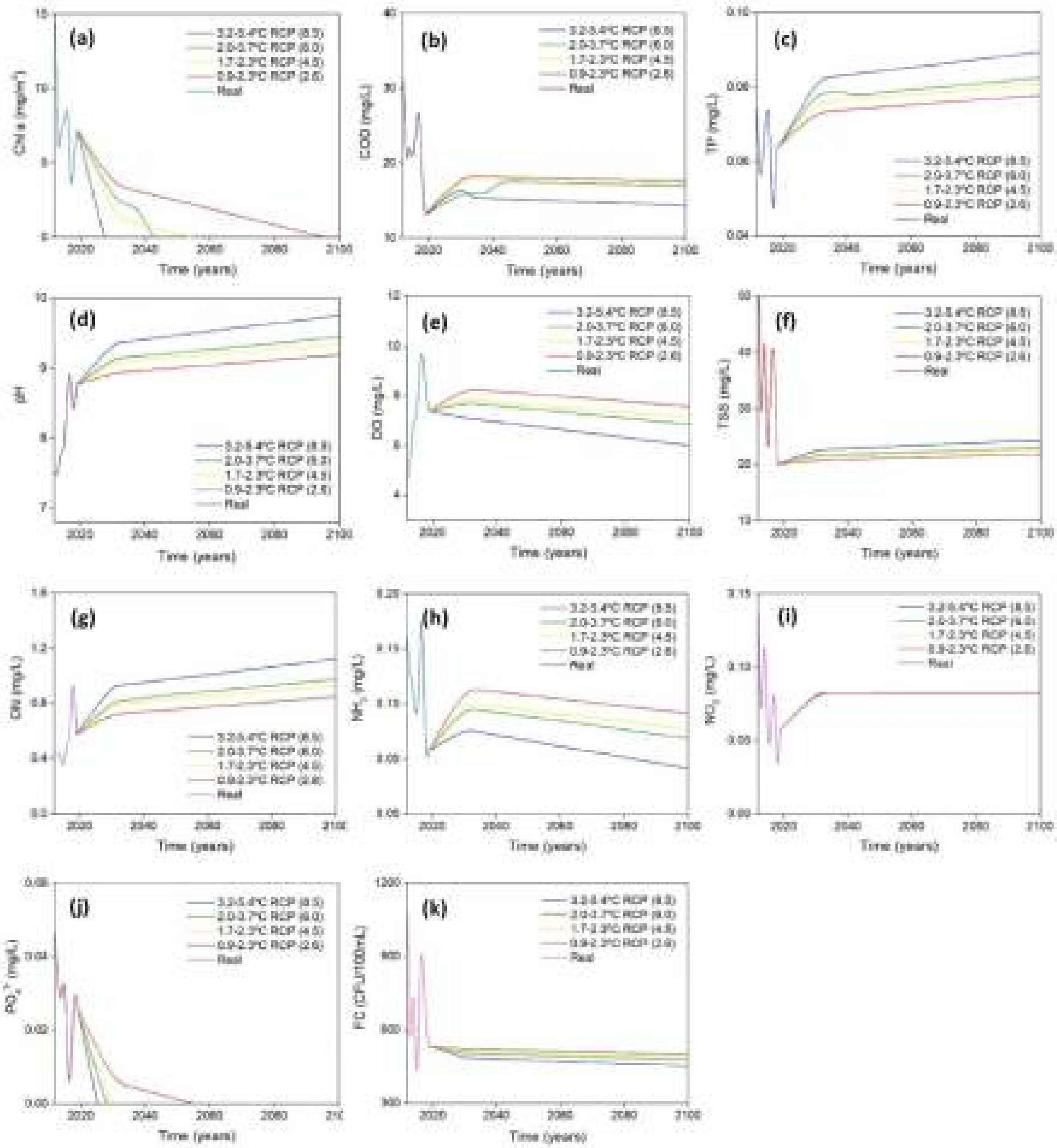

Fig. 4. Effect of different RCPs on water quality estimated using the proposed algorithms.

years based on regional climate. RCPs were useful describing temperature effect on critical water quality parameters and performed better than hydroclimatological simulations (Salimi and Scholz, 2021) by allowing a diagnosis of future trends over time.

Model calibration results showed statistical significance (e.g., $p < 0.05$) and high correlation in predicted values: R-square ranged 74.8%–99.9% (Table 1) for all cases rated as significant by other studies (Ambiga and Annadurai, 2015; Khatoon et al., 2013; Mustapha and Zaharin, 2012). After algorithm validation, forecasts were obtained for different WQI parameter, including simulated variations in parameter concentrations attributed to anthropogenic activities, to assess future water quality scenarios.

3.3. Temperature variations with global models

To assess WQI variation with temperature, four different temperature trajectories were modeled for each RCP until 2100. Table 2 shows the results of this assessment. Fig. 4 shows the effect of the different RCPs on water quality variables estimated using algorithms proposed in this study. As shown, RCP estimation showed an increase in bacterial load from 2030 to 2100 ranging from 469 CFU/100 mL (RCP 3.2–5.4 °C) to 510 CFU/100 mL (RCP 0.9–2.3 °C). The highest bacterial load was found for RCP 0.9–2.3 °C (510 CFU/100 mL), which resulted in predictions of AT in the range of 36–37 °C and WT in the 32–33 °C range. This trend is probably related to the optimal temperature for coliform bacteria growth (37 °C) because any temperature value below or above 37 °C will decrease bacterial growth. These results for bacterial load differ from other studies (Salimi and Scholz, 2021), which found that higher temperatures increased microbial growth and improved nutrient removal. As shown in Fig. 4e, DO decreased at higher temperatures, averaging 6.5 mg/L for RCP 3.2–5.4 °C and 7.9 mg/L for RCP 0.9–2.3 °C. The model predicted upward variation for pH, which increased considerably at higher temperatures, reaching 9.07 for RCP 3.2–5.4 °C. TSS and NO_3 did not show significant variation independently of RCP

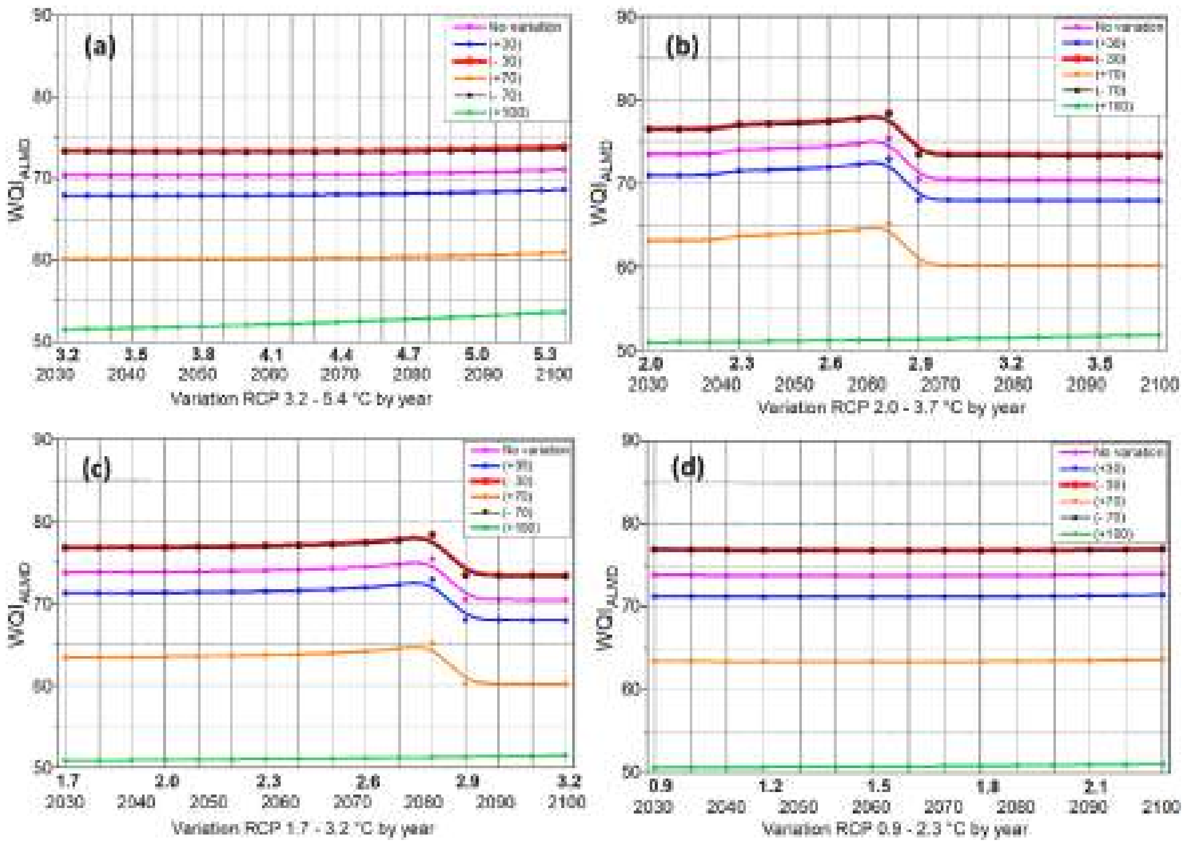

Fig. 5. WQI variations as a function of RCP scenarios: (a) 8.5, (b) 6.0, (c) 4.65, and (d) 2.6.

scenarios presenting slight ascending behavior over time, probably because of temperature effect on gas solubility, particulate material, nutrients, sediments and metabolic rate of aquatic organisms in the reservoir, increasing organic matter decomposition which produces increase in turbidity, nutrients and macrophyte growth and algal blooms directly related to TSS and nitrogen-related species (Chapman, 2021).

3.4. Future water quality scenarios

Several studies have attempted to show climate change impact on water quality (Gómez-Martinez et al., 2021; Exley et al., 2021) by simulating the effects of changes in hydroclimatological variables (e.g., precipitation, temperature) on parameters such as DO, TDS over time (Hassanjabbar et al., 2022). In this study, water quality in tropical water bodies was quantitatively evaluated to predict future scenarios through temperature changes from global climate change models. Fig. 5 shows four WQI scenarios obtained for different RCP trajectories: RCP 3.2–5.4 °C (Fig. 5a), RCP 2.0–3.7 °C (Fig. 5b), RCP 1.7–3.2 °C (Fig. 5c), and RCP 0.9–2.3 °C (Fig. 5d). A linear WQI trend was observed in all variations tested (±30, ±70, +100) as well as in RCP 3.2–5.4 °C without variation (Fig. 5a). To classify results, the rating scale used was excellent (WQI = 91–100), good (WQI = 71–90), medium (WQI = 51–70), poor (WQI = 26–50), and very bad (WQI = 0–25) as proposed elsewhere (Rajendran and Mansiya, 2015). The WQI showed variations in water quality parameters attributed to anthropogenic activities (FC, COD and TSS) increasing concentrations to +100, +70, and +30 (Fig. 4). When temperature oscillated within 3.2 °C and 4.4 °C, water quality was found medium. When temperature exceeded 4.5 °C, WQI went from medium to good and for variations −30 and −70, water quality was found good. Doubling average anthropogenic parameters concentration, WQI was significantly affected, moving from 71 (good) to 52 (medium) for the worst climate change scenario (Fig. 4).

For the worst-case scenario (+100), WQI was found without changes

Table 3
WQI_{ALMD} averages by RCP.

Average RCP interval (2030–2100)	WQI_{ALMD} average anthropogenic variation (2030–2100)					
	(normal)	(+30)	(-30)	(+70)	(-70)	(+100)
3.2–5.4 °C RCP 8.5	71	68	73	60	73	51
2.0–3.7 °C RCP 6.0	72	70	75	62	75	51
1.7–3.2 °C RCP 4.5	73	71	76	63	76	51
0.9–2.3 °C RCP 2.6	74	71	77	63	77	51

over time (e.g., 51 for 2030 and 54 for 2100), probably related to critical and sensitive parameters such as bacteria (FC) and primary productivity (Chl a, ON) in the reservoir. Results also suggest that organic parameters are directly related to increased temperature regardless of pollutant load tendency (Abdelrady et al., 2019). The best-case scenario was −30 (WQI = 73.5) followed by −70 (WQI = 73.2). No significant difference was found for −30 and −70 scenarios, probably because, under these conditions, pollutant load was at equilibrium with temperature and WQI dropped as pollutant load increases over −30.

Fig. 5 also shows scenarios with the highest pollutant load (+100 and + 70) generated the worst WQI results, identifying water quality as medium (51–70). On the other hand, scenarios −70 and −30 turned out generating the highest WQI values rated as good (71–90) (see pink lines in Fig. 5).

To analyze data from a general perspective, average WQI values were determined for variations of anthropogenic parameters (Table 3). Under normal conditions (e.g., without variations), WQI decreases as temperature increases. For all cases (+30, −30, +70, and −70), WQI was affected at higher temperatures. The proposed methodology aimed to offer an alternative for the quantitative water quality measurement in tropical reservoirs anywhere in the through implementation of WQI for tropical conditions. Because effects of climate change are generated global, identifying trends and forecasts for temperature impact on water quality is a significant effort. Climate change effects occur throughout earth's surface so, including impacts of anthropogenic activities and natural phenomena contributes to better managing water resources.

4. Conclusions

Through the application of statistical techniques, it was possible to generate a methodology to evaluate water quality in tropical reservoirs that included physicochemical and microbiological parameters as well as the effects of climate change to predict changes in the reservoir based on changes in temperature. The following are our main findings:

- The study provides a perspective on predicting water quality behavior of tropical reservoirs and vulnerability of water quality to anthropogenic activities in face of temperature variations generated by climate change. This offers an interesting overview of future trends for decision making.
- Based on fluctuations and forecasts obtained from the algorithms designed using this methodology, the influence of RCP trajectories proposed by global models is related to the expected increase in temperature in the coming years.
- Changes in water quality evaluated for the 2030–2100 period using the WQI suggested significant effect of high temperatures (WQI = 71 at 3.2–5.4 °C) with lower temperature producing improved WQI values (WQI = 74 at 0.9–2.3 °C).
- The application of multiparametric statistical tools, global climate change models and water quality indices provided alternatives for water quality modeling and predicting scenarios in tropical reservoirs.
- This paper proposes a tool to assess water quality through an index proposed for tropical areas sensitive to intrinsic characteristics of temperature variations.

Authors contribution statement

Alberto Quevedo-Castro: Quevedo-Castro contributed with investigation and writing—original draft preparation. Erick R. Bandala: Dr. Bandala contributed with formal analysis, supervision and visualization of the study as well as reviewing and editing the manuscript. Yaneth A. Bustos-Terrones: Bustos-Terrones contributed with investigation and writing—original draft preparation and supervision. Juan Gabriel Loaiza: Loaiza contributed with formal analysis and visualization. Jesús G. Rangel-Peraza: Rangel-Peraza contributed with visualization of the study.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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References

Abdelrady, A., Sharma, S., Sefelnasr, A., Abogbal, A., Kennedy, M., 2019. Investigating the impact of temperature and organic matter on the removal of selected organic micropollutants during bank filtration: a batch study. J. Environ. Chem. Eng. 7 (1), 102904.

Alias, R., Noor, N.A.M., Sidek, L.M., Kasa, A., 2021. Prediction of Water Quality for Free Water Surface Constructed Wetland Using ANN and MLRA.

Ambiga, K., AnnaDurai, R., 2015. Development of water quality index and regression model for assessment of groundwater quality. Int. J. Adv. Remote Sens. GIS 4 (1), 931–943.

Antunes, I.M.H.R., Albuquerque, M.T.D., Oliveira, S.F., Sánz, G., 2018. Predictive scenarios for surface water quality simulation-A watershed case study. Catena 170, 283–289.

APHA, 2017. Standard Methods for the Examination of Water and Wastewater, 23 ed. American Water Works Association, Washington DC.

Arab, S., Bouchelouche, D., Hamil, S., Arab, A., 2018. Application of water quality index for surface water quality assessment Boukourdane Dam, Algeria. In: In Conference of the Arabian J. Geosci, pp. 385–387.

Aslan-Yılmaz, A., Okuş, E., Övez, S., 2004. Bacteriological indicators of anthropogenic impact prior to and during the recovery of water quality in an extremely polluted estuary, Golden Horn, Turkey. Mar. Pollut. Bull. 49 (11–12), 951–958.

Atique, U., An, K.G., 2019. Reservoir water quality assessment based on chemical parameters and the chlorophyll dynamics in relation to nutrient regime. Pol. J. Environ. Stud. 28 (3).

Bai, X., Jiang, Y., Jiang, Z., Zhu, L., Feng, J., 2022. Nutrient potentiate the responses of plankton community structure and metabolites to cadmium: a microcosm study. J. Hazard Mater. 430, 128506.

Beltrán, A.R., Sánchez, P.J., Arroyo, B.G., 2015. Diagnóstico limnológico y pesquero de los principales embalses de Sinaloa. Editorial 672, 2015. ISBN:978-607-9423-41-4. http://biblioteca.diputados.gob.mx/janium/bv/cedrssa/lxii/diag_limpes_prinemb_sin.pdf. (Accessed 15 March 2021). Accessed.

Berhe, A.A., Barnes, R.T., Six, J., Marin-Spiotta, E., 2018. Role of soil erosion in biogeochemical cycling of essential elements: carbon, nitrogen, and phosphorus. Annu. Rev. Earth Planet Sci. 46 (1), 521–548.

Bouaroudj, S., Menad, A., Bounamous, A., Ali-Khodja, H., Gherib, A., Weigel, D.E., Chenchouni, H., 2019. Assessment of water quality at the largest dam in Algeria (Beni Haroun Dam) and effects of irrigation on soil characteristics of agricultural lands. Chemosphere 219, 76–88.

Bouraï, L., Logez, M., Laplace-Treyture, C., Argillier, C., 2020. How do eutrophication and temperature interact to shape the community structures of phytoplankton and fish in lakes? Water 12 (3), 779.

Buytaert, W., De Bièvre, B., 2012. Water for cities: the impact of climate change and demographic growth in the tropical Andes. Water Resour. Res. 48 (8).

Chapman, D., 2021. Water Quality Assessments: a Guide to the Use of Biota, Sediments and Water in Environmental Monitoring. CRC Press.

CONAGUA (Comisión Nacional del Agua), 2021. Monitoreo de las principales presas en México. CONAGUA, Subdirección General de Administración del Agua, Gerencia de Planificación Hídrica. Sistema Nacional de Información del Agua (SINA). http://sina.conagua.gob.mx/sina/. (Accessed 10 February 2021). Accessed.

Cude, C.G., 2001. Oregon water quality index a tool for evaluating water quality management effectiveness 1. JAWRA J. Am. Water Resour. Assoc. 37 (1), 125–137.

Danladi Bello, A.A., Hashim, N.B., Mohd Haniffah, M.R., 2017. Predicting impact of climate change on water temperature and dissolved oxygen in tropical rivers. Climate 5 (3), 58.

De la Mora-Orozco, D., Flores-Lopez, H., Rubio-Arias, H., Chavez-Duran, A., Ochoa-Rivero, J., 2017. Developing a water quality index (WQI) for an irrigation dam. Int. J. Environ. Res. Publ. Health 14 (5), 439.

Delpla, I., Jung, A.V., Baures, E., Clement, M., Thomas, O., 2009. Impacts of climate change on surface water quality in relation to drinking water production. Environ. Int. 35 (8), 1225–1233.

Exley, G., Armstrong, A., Page, T., Jones, I.D., 2021. Floating photovoltaics could mitigate climate change impacts on water body temperature and stratification. Sol. Energy 219, 24–33.

Fang, X., Li, X., Zhang, Y., Zhao, Y., Qian, J., Hao, C., Wu, Y., 2021. Random forest-based understanding and predicting of the impacts of anthropogenic nutrient inputs on the water quality of a tropical lagoon. Environ. Res. Lett. 16 (5), 055003.

Geng, M., Wang, K., Yang, N., Li, F., Zou, Y., Chen, X., Xie, Y., 2021. Evaluation and variation trends analysis of water quality in response to water regime changes in a typical river-connected lake (dongting lake), China. Environ. Pollut. 268, 115761, 115761.

Gómez-Martínez, G., Galiano, L., Rubio, T., Prado-López, C., Redolat, D., Paradinas Blázquez, C., Macián Cervera, J., 2021. Effects of climate change on water quality in the Jucar river basin (Spain). Water 13 (17), 2424.

Grbčić, L., Družeta, S., Mauša, G., Lipić, T., Lušić, D.V., Alvir, M., Kranjčević, L., 2021. Coastal Water Quality Prediction Based on Machine Learning with Feature Interpretation and Spatio-Temporal Analysis arXiv preprint arXiv:2107.03230.

Guillen, L., Oliveira, F., Valente-Neto, F., Koroiva, R., Forsin, D., Fernandes, D., Ubiratan, L., Kuhlmann, M., Sundar, S., Covich, A., Pereira, J., 2021. Large-scale prediction of tropical stream water quality using Rough Sets Theory. Ecol. Inf. 61, 101226.

Guo, D., Thomas, J., Lazaro, A.B., Matwewe, F., Johnson, F., 2021a. Modelling the influence of short-term climate variability on drinking water quality in tropical developing countries: a case study in Tanzania. Sci. Total Environ. 763, 142932.

Guo, M., Ma, S., Wang, L.J., Lin, C., 2021b. Impacts of future climate change and different management scenarios on water-related ecosystem services: a case study in the Jianghuai ecological economic Zone, China. Ecol. Indicat. 127, 107732.
Guo, M., Ma, S., Wang, L.J., Lin, C., 2021c. Impacts of future climate change and different management scenarios on water-related ecosystem services: a case study in the Jianghuai ecological economic Zone, China. Ecol. Indicat. 127, 107732.
Hassanjabbar, A., Nezaratian, H., Wu, P., 2022. Climate change impacts on the flow regime and water quality indicators using an artificial neural network (ANN): a case study in Saskatchewan, Canada. J. Water Clim. Change 13 (8), 3046–3060.
Imneisi, I.B., Aydin, M., 2016. Water quality index (WQI) for main source of drinking water (Karaçomak Dam) in Kastamonu City, Turkey. J. Environ. Anal. Toxicol. 6 (407), 2161, 0525.
IPCC, 2018. Resumen para responsables de políticas. En: Calentamiento global de 1,5 °C, Informe especial del IPCC sobre los impactos del calentamiento global de 1,5 °C con respecto a los niveles preindustriales y las trayectorias correspondientes que deberían seguir las emisiones mundiales de gases de efecto invernadero, en el contexto del reforzamiento de la respuesta mundial a la amenaza del cambio climático, el desarrollo sostenible y los esfuerzos por erradicar la pobreza. https://www.ipcc.ch/site/assets/uploads/sites/2/2019/09/IPCC-Special-Report-1.5-SPM_es.pdf. (Accessed 13 May 2021). Accessed.
Jayakody, P., Parajuli, P.B., Cathcart, T.P., 2014. Impacts of climate variability on water quality with best management practices in sub-tropical climate of USA. Hydrol. Process. 28 (23), 5776–5790.
Jia, Y., Schmid, C., Shuliakevich, A., Hammers-Wirtz, M., Gottschlich, A., der Beek, T., Hollert, H., 2019. Toxicological and ecotoxicological evaluation of the water quality in a large and eutrophic freshwater lake of China. Sci. Total Environ. 667, 809–820.
Khatoon, N., Khan, A.H., Rehman, M., Pathak, V., 2013. Correlation study for the assessment of water quality and its parameters of Ganga River, Kanpur, Uttar Pradesh, India. IOSR J. Appl. Chem. 5 (3), 80–90.
Korkanç, S.Y., Kayıkçı, S., Korkanç, M., 2017. Evaluation of spatial and temporal water quality in the Akkaya dam watershed (Niğde, Turkey) and management implications. J. Afr. Earth Sci. 129, 481–491.
Kothari, V., Vij, S., Sharma, S., Gupta, N., 2021. Correlation of various water quality parameters and water quality index of districts of Uttarakhand. Environ. Sustain. Indic. 9, 100093.
Kumar, P., Lai, H., Wong, J., Syuhadaa, N., Kamal, M., Abdulmohsin, H., Ahmed, A., Sherif, M., Sefelnasr, A., El-Shafie, A., 2020. Review of nitrogen compounds prediction in water bodies using artificial neural networks and other models. Sustainability 12, 4359.
Li, B., Wan, R., Yang, G., Wang, S., Wagner, P.D., 2020. Exploring the spatiotemporal water quality variations and their influencing factors in a large floodplain lake in China. Ecol. Indicat. 115, 106454.
Loaiza, J.G., Rangel-Peraza, J.G., Sanhouse-García, A.J., Monjardín-Armenta, S.A., Mora-Félix, Z.D., Bustos-Terrones, Y.A., 2021. Assessment of water quality in A tropical reservoir in Mexico: seasonal, spatial and multivariable analysis. Int. J. Environ. Res. Publ. Health 18 (14), 7456.
Majedul, I.M.M., Iqbal, M.S., Leemans, R., 2018. Hofstra N. Modelling the impact of future socio-economic and climate change scenarios on river microbial water quality. Int. J. Environ. Res. Publ. Health 221, 283–292.
Me, W., Hamilton, D., McBride, C., Abell, J., Hicks, B., 2018. Modelling hydrology and water quality in a mixed land use catchment and eutrophic lake: effects of nutrient load reductions and climate change. Environ. Model. Software 109, 114–133.
Mena-Rivera, L., Salgado-Silva, V., Benavides-Benavides, C., Coto-Campos, J.M., Swinscoe, T.H., 2017. Spatial and seasonal surface water quality assessment in a tropical urban catchment: Burío River, Costa Rica. Water 9 (8), 558.
Messina, N.J., Couture, R., Norton, S.A., Birkel, S.D., Amirbahman, A., 2020. Modeling response of water quality parameters to land-use and climate change in a temperate, mesotrophic lake. Sci. Total Environ. 713, 136549.
Muñoz-Nájera, M.A., Tapia-Silva, F.O., Barrera-Escorcia, G., Ramírez-Romero, P., 2020. Statistical and geostatistical spatial and temporal variability of physico-chemical parameters, nutrients, and contaminants in the Tenango dam, Puebla, Mexico. J. Geochem. Explor. 209, 106435.
Mustapha, A., Zaharin, A., 2012. Multivariate statistical analysis and environmental modeling of heavy metals pollution by industries. Pol. J. Environ. Stud. 21 (5), 1359–1367.
Negri, A., Smith, R., King, O., Frangos, J., Warne, M., Uthicke, S., 2020. Adjusting tropical marine water quality guideline values for elevated ocean temperatures. Environ. Sci. Technol. 54 (2), 1102–1110, 2020.
Ni, Z., Wu, X., Li, L., Lv, Z., Zhang, Z., Hao, A., Li, C., 2018. Pollution control and in situ bioremediation for lake aquaculture using an ecological dam. J. Clean. Prod. 172, 2256–2265.
Novotny, V., 2002. Water Quality: Diffuse Pollution and Watershed Management. John Wiley and Sons.
Okyereh, S.A., Ofosu, E.A., Kabobah, A.T., 2019. Modelling the impact of Bui dam operations on downstream competing water uses. Water-Energy Nexus 2 (1), 1–9.
Quang, D., Tran, D., Duc, T., Pham, S., 2019. Predicting water quality responses under climate change using coupled one- and two-dimensional models for Dong Nai River Basin. In: Conference: 15th International Asian Urbanization Conference (AUC)At. Vietnamese-German University (VGU) in Ho Chi Minh City, Vietnam.
Quevedo-Castro, A., Bandala, E.R., Rangel-Peraza, J.G., Amábilis-Sosa, L.E., Sanhouse-García, A., Bustos-Terrones, Y.A., 2019. Temporal and spatial study of water quality and trophic evaluation of a large tropical reservoir. Environments 6 (6), 61.
Quevedo-Castro, A., Rangel-Peraza, J.G., Bandala, E., Amabilis-Sosa, L., Rodríguez-Mata, A., Bustos-Terrones, Y., 2018. Developing a water quality index in a tropical reservoir using a measure of multiparameters. J. Water, Sanit. Hyg. Dev. 8, 752–766.
Rajendran, A., Mansiya, C., 2015. Physico-chemical analysis of ground water samples of coastal areas of south Chennai in the post-Tsunami scenario. Ecotoxicol. Environ. Saf. 121, 218–222.
Rocha, C.H., Casquin, A.P., Pereira, R.O., 2019. Correlations chart: tool to analyse the dynamics of water quality parameters. Rev. Bras. Eng. Agrícola Ambient. 23, 383–390.
Saber, A., James, D.E., Hannoun, I.A., 2020. Effects of lake water level fluctuation due to drought and extreme winter precipitation on mixing and water quality of an alpine lake, case study: lake arrowhead, California. Sci. Total Environ. 714, 136762.
Saha, A., Ramya, V.L., Jesna, P.K., Mol, S.S., Panikkar, P., Vijaykumar, M.E., Das, B.K., 2021. Evaluation of spatio-temporal changes in surface water quality and their suitability for designated uses, Mettur Reservoir, India. Nat. Resour. Res. 30 (2), 1367–1394.
Sajjadi, S., Zolfaghari, G., Adab, H., Allahabadi, A., Delsouz, M., 2017. Measurement and modeling of particulate matter concentrations: applying spatial analysis and regression techniques to assess air quality. MethodsX 4, 372–390.
Salimi, S., Scholz, M., 2021. Impact of future climate scenarios on peatland and constructed wetland water quality: a mesocosm experiment within climate chambers. J. Environ. Manag. 289, 112459.
Shil, S., Singh, U.K., Mehta, P., 2019. Water quality assessment of a tropical river using water quality index (WQI), multivariate statistical techniques and GIS. Appl. Water Sci. 9 (7), 1–21.
Sidabutar, N.V., Namara, I., Hartono, D.M., Soesilo, T.E.B., 2017, May. The effect of anthropogenic activities to the decrease of water quality. In: IOP Conference Series: Earth and Environmental Science, vol. 67. IOP Publishing, 012034. No. 1.
Simonetti, V.C., Frascareli, D., Gontijo, E.S., Melo, D.S., Friese, K., Silva, D.C., Rosa, A.H., 2021. Water quality indices as a tool for evaluating water quality and effects of land use in a tropical catchment. Int. J. River Basin Manag. 19 (2), 157–168.
Tiyasha, Tung T.M., Yaseen, Z.M., 2021. Deep learning for prediction of water quality index classification: tropical catchment environmental assessment. Nat. Resour. Res. 30, 4235–4254.
Tripathi, B., Pandey, R., Raghuvanshi, D., Singh, H., Pandey, V., Shukla, D.N., 2014. Studies on the physico-chemical parameters and correlation coefficient of the river Ganga at holy Place Shringverpur, Allahabad. J. Environ. Sci., Toxicol. Tood Technol. 8 (10), 29–36.
Uriarte, M., Yackulic, C.B., Lim, Y., Arce-Nazario, J.A., 2011. Influence of land use on water quality in a tropical landscape: a multi-scale analysis. Landsc. Ecol. 26 (8), 1151–1164.
Vasistha, P., Ganguly, R., 2020. Water quality assessment of natural lakes and its importance: an overview. Mater. Today Proc. 32, 544–552.
Xu, Z., Cai, X., Yin, X., Su, M., Wu, Y., Yang, Z., 2019. Is water shortage risk decreased at the expense of deteriorating water quality in a large water supply reservoir? Water Res. 165, 114984.
Yaghoubi, B., Hosseini, S.A., Nazif, S., Daghighi, A., 2020. Development of reservoir's optimum operation rules considering water quality issues and climatic change data analysis. Sustain. Cities Soc. 63, 102467.
Yang, N., Zhang, C., Wang, L., Li, Y., Zhang, W., Niu, L., Wang, L., 2021. Nitrogen cycling processes and the role of multi-trophic microbiota in dam-induced river-reservoir systems. Water Res. 206, 117730.