

Long-Term Monitoring of Cyclic Climate Variations to Assess Nutrient-Driven Chlorophyll-a (Chla) Dynamics in Highland Eutrophic Lake Erhai in China

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Abstract

Eutrophication due to nutrient enrichment is a global phenomenon. Climate cycles may enhance chlorophyll-a (Chla) and algal blooms, but climate-nutrient interactions remain unclear. This study monitors long-term climate variations of nutrient-driven effects on Chla in eutrophic Erhai Lake (China) using 1988–2018 data from 10 sites. Air temperature (AT) increased at 0.8°C/decade in each 4–6-year cycle, with a relatively modest change in the last cycle (2013–2018); wind speed (WS) declined 30% (2.5→1.8 m/s). TN/TP increased from 485 to 534 µg/L and 20 to 29 µg/L, respectively by 2006 and then stabilized. SD remained stable initially then decreased to 1.7 m in 2001–2003. GAM analysis showed Chla strongly correlated with TN ($p < 0.001$) all seasons, TP ($p < 0.05$) summer-only, AT ($p < 0.001$) winter-only. The interaction of cyclic climate variations with nutrient levels contributed to amplifying Chla concentrations and algal blooms in Erhai Lake. As Erhai Lake serves as a primary drinking-water source for the surrounding population, the monitoring-based assessment of climate-nutrient-chla interactions provide scientific foundation for sustainable lake management and supports Sustainable Development Goal 6 (clean water and sanitation) in rapidly developing highland regions.

1. Introduction

The substantial enrichment of nutrients leading to eutrophication poses a significant global challenge in managing freshwater resources. In recent decades, research has primarily focused on understanding the phytoplankton responses to nutrient enrichment in lakes. Nevertheless, scientific predictions proved that rising water temperatures due to climate change could enhance phytoplankton biomass and Chla concentration (Rigosi et al., 2015). Climate change is considered a likely catalyst for the global increase in lake phytoplankton blooms since the 1980s (Ho et al., 2019). Consequently, efforts in lake management must investigate how phytoplankton growth responds to nutrients under the influence of climate change. Nevertheless, the overall influence of climate and nutrients on Chla and phytoplankton is still questionable. Finding answers to such uncertainties is important for designing effective strategies for sustainable lake management.

Chlorophyll-a (Chla) is an important indicator to assess algal blooms and growth of phytoplankton in lakes. Nutrient concentrations, such as phosphorus (P) and nitrogen (N), are considered as major factors responsible for increased Chla concentrations in lakes (Li et al., 2017; Li et al., 2019; Filazzola et al., 2020; Lin et al., 2021; H. Wang et al., 2020). On the other hand, the climatic factors, such as atmospheric temperature and wind speed, also contribute to annual and seasonal fluctuations of Chla concentration (Ho and Michalak, 2019). Wind speed (WS) impacts the physical, chemical, and biological processes of lakes, such as sediment suspension, water clarity and nutrient concentrations in shallow lakes (Tang et al., 2020). WS also affects the movement, mixing, and colony formation processes of phytoplankton (Jalil et al., 2021; Wang et al., 2021). Atmospheric temperature increases algal growth, pulls them up to the surface and supports bloom formation (Wang et al., 2021; Zou et al., 2021). The significant climate variations may further enhance this process (Frank et al., 2023; Ligorini et al., 2023) and becomes primary drivers for fluctuations in nutrient-Chla relationships. Understanding the interactive impact of

climate and nutrients on Chla is very challenging due to high geographical heterogeneity of climate change (Adu-Prah et al., 2019; Piccolroaz et al., 2020; Woolway et al., 2021). Monitoring and assessment of such complex interactions are important for effective environmental management.

Simple statistical methods were employed using short term data and/or lake-specific water quality models were employed to study interactive impacts of nutrients and climate change on Chla in various studies (Wu et al., 2016; Thomas et al., 2018; Tasnim et al., 2021). Rigosi et al. (2015) investigated the combined impacts of nutrients and climate on cyanobacterial blooms using approximately 10 years data across 20 lakes with diverse characteristics. Chla response to nutrients due to climate change was quantified using 10 years dataset in 26 lakes (Huo et al., 2019).

Multi-lake studies generally identify broad patterns, while single-lake analyses focus on site-specific mechanisms which are usually important for local management. Highland Erhai Lake with 2,500m elevation and subtropical monsoon climate offers a unique climate-nutrient environment which are not considered in regional analyses, and thus reduce ecological fallacy (Johnson & Chess, 2006; Maas-Hebner et al., 2015). Liang et al. (2020) studied significant variations in regional and site-specific nutrient-Chla relationships and discovered the existence of ecological fallacy within each ecoregion. Studying site-specific stressor-response relationships utilizing long-term monitoring data can effectively mitigate ecological delusions and offer robust and reliable information for lake-specific management decisions.

Improved software technology and advanced computational capabilities have enabled scientists to utilize advanced statistical tools to predict long-term environmental changes. Scientists counted on parametric models to predict algal blooms in lakes (Rousso et al., 2020). Wu et al. (2022) studied relationships between modelled nutrient cycling fluxes and the lakes' physical characteristics by employing Generalized Linear Model (GLM) to assess 596 lakes. Perez-Ruzafa et al. (2019) investigated variations in Chla and water transparency by applying GLM with stepwise forward selection of variables. However, the empirical analysis may raise limitations in understanding understanding the combined effects of climate change and nutrients on phytoplankton growth due to monthly and/or annual variations in intricate biomass and community dynamics of phytoplankton with significant seasonal and interannual variations in nutrient and climatic factors. A reliable analytical framework can reduce the uncertainty induced by stressor and response variability. Long-term data with high time resolution can increase our understanding about the hierarchical ordering of factors contributing to variability. The Generalized Additive Model (GAM) proves more accurate in predicting dependent variables for extended time series data compared to linear models.

The interactive effects of nutrient concentrations and climatic factors on Chla concentrations and algal blooms in previous studies were often unnoticed which reduce a comprehensive understanding of lake management. We, as in this study, hypothesize that quantifying the interactive effects of nutrients and climatic factors and estimating the response of phytoplankton biomass or Chla to such factors would enhance our knowledge of lake eutrophication, which would be crucial for effective lake management

decisions, particularly under warmer conditions. Therefore, we employed GAM to explore the relationship between these major influencing factors and Chla.

The mechanism studied in Erhai Lake, such as the interactions between air temperature, wind dynamics, nutrient availability, and phytoplankton biomass are not unique to this system. Shallow and polymictic lakes worldwide are increasingly exposed to similar events of climatic changes and nutrient legacies. Our study integrated long-term observations with generalized additive models providing a process-oriented framework that can be applied to other lake systems to assess climate–nutrient interactions and bloom susceptibility under changing environmental conditions.

Since Erhai Lake is the major drinking-water source for Dali City and supports agriculture, tourism, and local livelihoods across its basin, safeguarding Erhai Lake's water quality is also a development priority beyond its ecological significance. Poor water quality threatens aquatic ecosystems and impacts public health and regional socio-economic development. Understanding the impacts of climatic variability and nutrient loading on Chla dynamics is important for the sustainable management of water resources and integration of economic development with environmental protection in fast-growing plateau regions of China and elsewhere. This study involves a robust 30-year monitoring dataset and utilization of GAM as an assessment tool to identify stressor-response relationships. This research also improves methodological understanding for long-term monitoring, assessment of climate-nutrient interactions and adaptive water quality management in Erhai Lake and other lake systems.

2. Data and methods

2.1 Study region and data

Erhai Lake is located on Yunnan-Guizhou Plateau in Southwest China, at 100°05′–100°17′N and 25°36′–25°58′E (Fig. 1). Erhai Lake has a surface area of 247.42 km² and a volume of 29.59 × 10⁸ m³. It has a maximum depth of 21.3 m, with an average depth of 10.8 m. The lake's catchment area covers 2,565 km² and includes 117 tributary inflows, with a single outflow river in the Erhai Basin.

Starting from the early 1980s, the Dali County Environmental Monitoring Center initiated site-specific observations encompassing physical, chemical, and biological parameters, which stands as one of the earliest instances of site-specific limnological observations in China.

Since the beginning of 1980s, the Dali County Environmental Monitoring Center conducted site-specific observation involving physical, chemical, and biological parameters, which is one of the earliest available limnological site-specific observations in China.

Analysis utilized long-term data spanning from 1988 to 2018, encompassing observations of total nitrogen (TN), total phosphorus (TP), Secchi depth (SD), chlorophyll-a (Chla), and surface water air temperature (AT) collected at ten sites (EH1 – EH10, as illustrated in Fig. 1). Seasonal sampling was done in March, August, and November during the period from 1988 to 2002, shifting to monthly sampling

from 2003 to 2018. The assessment of water quality trends involved the calculation of seasonal and yearly mean concentrations derived from observations at the ten sites.

For the period spanning 1988 to 2018, daily meteorological data, encompassing maximum, minimum, and mean air temperatures, along with maximum and mean wind speeds and precipitation, were gathered from the Dali meteorological station (MT in Fig. 1), recognized as a Chinese National Meteorological Basic Station, positioned approximately 700 m offshore (100°18'N, 25°7'E) at an elevation of 1,990.5 m. Monthly, seasonal, and yearly meteorological parameters were computed based on the daily observations.

2.1.1. Monitoring design and protocol

Ten fixed sampling sites (EH1–EH10), representing significant inflow/outflow zones and spatial variability were selected as part of the monitoring design. To improve temporal resolution for evaluation, sampling frequency was seasonal (March, August, November) from 1988 to 2002 and monthly from 2003 to 2018. Standard procedures were followed throughout the monitoring period, and yearly interlaboratory calibration exercises were carried out. Regular equipment calibration, approved reference materials, and duplicate analyses were used to ensure data quality.

2.2 Trend analysis

As a nonparametric method for trend testing, the Mann-Kendall (M-K) test had an extensive application in detecting monotonic trends in timeseries of hydroclimatic and water quality factors (Li et al., 2020; Peng et al., 2021). To mitigate potential errors in trends due to serial autocorrelation and to ensure more robust trend analysis, the M-K test was employed in combination with the free pre-whitening method (Yue and Wang, 2002).

2.2.1 Cycle Detection

Spectral analysis or periodogram was used to identify periodic cycles on detrended time series, which confirmed 4–6 year temperature cycles and 5–7 year wind cycles. Cycles were validated by GAM smooth functions (edf > 1.0).

2.3 Generalized Additive Model (GAM)

The Generalized Additive Model (GAM) is a parametric data-driven regression model designed to enhance the accuracy of predicting dependent variables by incorporating non-linear functions. It is particularly effective in improving predictions for long time series data. In our study, GAM was employed to investigate the relationship between two major influencing factors and chlorophyll- α . The predictive variables encompassed concentrations of total nitrogen, total phosphorus, quarterly mean air temperature, and water level, while chlorophyll- α concentrations served as the response variable. Before modeling, non-normally distributed response variables underwent log transformation. For function fitting

and prediction using R software, the 'mgcv' package was utilized, and GAM was parameterized in accordance with the technical recommendations outlined by Simpson and Anderson (2009). F-tests were employed to analyze GAM results, revealing statistical significance ($P \leq 0.05$) across all variables. COD was excluded from GAM due to collinearity with Chla ($r = 0.82$, $p < 0.001$; Figs. 3–4). The robustness of the GAM model was checked through diagnostic plots depicting residuals and fitted values, as well as plots illustrating residuals and time.

3. Results

3.1 Climate change analysis

A 30-year (1988–2018) long-term monitoring dataset is illustrated in Fig. 2, which shows changes in temperature, surface wind speed, and water level in Erhai Lake. A cyclical upward trend in temperatures is observed (Fig. 29a). Each temperature cycle covers 4–6 years. The average temperature in each succeeding cycle seems to be increasing than the previous cycle. However, the dynamics changed in the last cycle (2013–2018), marked by a relatively gentle temperature change, and the highest peak did not exceed the previous cycle. Over the period from 1988 to 2018, the annual minimum, maximum, and average air temperatures around Erhai Lake fluctuated around 11 °C, 22 °C, and 14 °C, respectively. Notably, a significant warming trend was observed, with warming rates of 0.45 °C/decade, 0.51 °C/decade, and 0.37 °C/decade for the annual average, maximum, and minimum temperatures, respectively. Additionally, the warming rate exhibited seasonal variability (Table 1), with the highest warming rate recorded in the seasonal average air temperature during winter, followed by spring (0.66 °C/decade), summer (0.41 °C/decade), and autumn (0.27 °C/decade).

The annual average wind speed exhibited periodic changes and slightly decreased with 0.14 m s^{-1} per decade ($R^2 = 0.68$, $P < 0.001$) from 1988 to 2018 (Fig. 2b). Wind speed fluctuated within a range of approximately 2.5 m s^{-1} over each 5–7-year cycle. Although the difference between the peaks and troughs within each cycle was minimal, an anomaly emerged between 2014 and 2018. During this period, 2016 with the lowest, while 2014 and 2018 had the highest annual average wind speed within the cycle.

Furthermore, the annual maximum wind speed displayed a declining trend, with slopes of -0.20 m s^{-1} per decade ($R^2 = 0.39$, $P < 0.001$), reducing from 7.5 to 6.0 m s^{-1} . Between 1988 and 1998, the annual maximum wind speed consistently remained above 7.0 m s^{-1} . However, in 1999, for the first time, the annual maximum wind speed dropped significantly below 7.0 m s^{-1} . Notably, after 2010, the annual maximum wind speed consistently remained below 7.0 m s^{-1} , fluctuating between 5.2 and 6.9 m s^{-1} .

In contrast to the earlier period (1988–2009), wind speed declined in later years, as illustrated in Fig. 2b. Erhai Lake's water level, while generally maintaining a flat profile amid periodic fluctuations, with a tendency for the annual average and annual minimum water levels to rise initially. Particularly, the annual minimum water level demonstrated rapid periodic increases. Post-2009, the annual average, minimum,

and maximum water levels gradually stabilized in subsequent years, except for the annual minimum water level, which showed fluctuations in 2014 (Fig. 2c).

Long-term (30 years) monitoring results revealed: a) a rise of 1.35 °C and 1.62 °C in the annual average and maximum air temperatures, respectively, over the past three decades; b) a 30% decrease in wind speed during the same period; and c) an overall increase in lake water levels over the past 30 years, with no significant change noted in the last decade.

3.2 Trend of nutrient and Chla concentrations

From 1988 to 2018, various water quality parameters in Erhai Lake, including TN, TP, $\text{NH}_4^+\text{-N}$, COD, and transparency, measured as Secchi Depth (SD), were examined. Notably, over the past 30 years, the TN concentration in Erhai Lake doubled. Initially, TN concentration increased rapidly from 1988 to 2006, followed by a period of stability from 2006 to 2018. Similarly, the TP concentration increased from 0.018 mg L^{-1} to 0.33 mg L^{-1} in 2003, followed by a subsequent decrease in the succeeding years. The concentrations of $\text{NH}_4^+\text{-N}$ were stable during the first 13 years, rapidly increased from 2001 to 2006, and after decline for almost a decade, the concentrations stabilized again. COD increased rapidly from 1995 to 2003, then decreased, and later showed an increasing trend. SD remained consistent at 3.3 m to 4.4 m during the initial 13 years but rapidly declined to around 1.7 m in 2001–2003. The overall trends indicate that TN, TP, $\text{NH}_4^+\text{-N}$, COD, and SD rapidly changed until around 2000, after which they showed a trend of relative stability post-2007 (Fig. 3 and Fig. 4).

Chlorophyll-a (Chla) concentration is considered as indicator of algae biomass. A 30-years monitoring period of Erhai Lake, the Chla concentration showed a distinct progress over this period, which can be divided in three key stages. During the initial phase from 1998 to 2001, the Chla concentrations were low, fluctuating around 1 $\mu\text{g L}^{-1}$. Subsequently, in 2001, there was a rapid surge in Chla concentration, reaching highest at 23.4 $\mu\text{g L}^{-1}$ in 2003, followed by a subsequent minor decrease within the range of 5 to 14 $\mu\text{g L}^{-1}$.

3.3 Chla concentration in relation to climatic and nutrient factors

The Chla concentrations throughout the entire study period were categorized into four trophic states: oligotrophic ($\text{Chla} < 2 \mu\text{g L}^{-1}$), mesotrophic ($2 \leq \text{Chla} < 7 \mu\text{g L}^{-1}$), eutrophic ($7 \leq \text{Chla} < 30 \mu\text{g L}^{-1}$), and hyper-eutrophic ($\text{Chla} \geq 30 \mu\text{g L}^{-1}$). The logarithms of total nitrogen (TN) and total phosphorus (TP) during these states were plotted in Fig. 5, revealing an increasing trend in both N and P with rising Chla concentrations.

Table 1 presents the concentrations averaged over the 30-year period for Chla, TP, TN, and N/P ratios in the spring, summer, autumn, and winter seasons. The data indicates that average Chla concentrations were 12.2 ± 11.1 and $14.9 \pm 13.3 \mu\text{g L}^{-1}$, representing an increase of almost $\geq 100\%$ during summer and

autumn, respectively, compared to the spring season ($6.68 \pm 3.74 \mu\text{g L}^{-1}$), while it decreased again in the winter ($9.81 \pm 4.83 \mu\text{g L}^{-1}$). Similarly, a 30% increase in TP was observed in summer and autumn. TN increased by 7–10% in summer and autumn, followed by a decrease in winter at similar rates. In contrast, the N/P ratio decreased by 37% in summer and autumn compared to spring and then increased by 45% in winter. Comparing the seasonal variability of TP and TN with Chla, it is evident that Chla variation is consistent with TP and TN trends.

The average maximum and minimum temperatures for the thirty-year span during summers were $25.2 \pm 0.98 \text{ }^{\circ}\text{C}$ and $16.5 \pm 0.61 \text{ }^{\circ}\text{C}$, respectively, with an overall average temperature of $20.0 \pm 0.77 \text{ }^{\circ}\text{C}$ (Table 2). In contrast, the average winter temperature dropped as low as $4.35 \pm 1.25 \text{ }^{\circ}\text{C}$. The average wind speed during summers was the lowest at $1.58 \pm 0.23 \text{ m s}^{-1}$ compared to the spring and winter seasons.

Table 1
Seasonal average (Mean $\pm$ SD) Chla and nutrients concentration

Season	Chla	TP	TN	N/P
	----- $\mu\text{g L}^{-1}$ -----			
Spring	6.68 ± 3.74	20.4 ± 7.39	485.9 ± 154.7	25.9 ± 11.1
Summer	12.2 ± 11.1	29.2 ± 11.3	522.7 ± 223.6	18.9 ± 7.91
Autumn	14.9 ± 13.3	29.1 ± 15.3	534.4 ± 205.3	20.6 ± 9.39
Winter	9.81 ± 4.83	19.6 ± 6.82	494.3 ± 120.8	29.7 ± 19.4

Table 2
Seasonal average (Mean $\pm$ SD) climatic data

Season	Max Temp	Min Temp	Av Temp	Ave wind	Max wind	Rainfall
	----- $^{\circ}\text{C}$ -----			----- m s^{-1} -----		mm
Spring	22.8 ± 2.20	10.9 ± 2.60	16.5 ± 2.34	3.03 ± 0.65	7.89 ± 1.58	47.9 ± 50.6
Summer	25.2 ± 0.98	16.5 ± 0.61	20.0 ± 0.77	1.58 ± 0.23	4.79 ± 0.55	183.7 ± 77.4
Autumn	21.1 ± 2.45	10.7 ± 3.58	14.8 ± 2.94	1.70 ± 0.37	4.95 ± 0.96	74.3 ± 68.3
Winter	17.1 ± 1.44	4.35 ± 1.25	9.94 ± 1.40	2.96 ± 0.75	7.83 ± 1.62	21.8 ± 23.5

After analyzing the annual and seasonal trends of nutrients, climate factors, and Chla, we employed the Generalized Additive Model (GAM) to investigate the contributions of explanatory variables, including TN, TP, AT, and MWS, to the long-term trends and seasonal variability of Chla in Erhai Lake (Fig. 6). The responses are depicted in both Fig. 6 and Table 3. GAM analysis revealed a robust relationship ($P < 0.001$) between Chla and TN during the spring, summer, and winter seasons. TP exhibited a positive

correlation ($P < 0.05$) with Chla solely in the summer season. Additionally, the average AT demonstrated a significant relationship ($P < 0.001$) with Chla during the winter season only (Table 3).

Table 3
The GAM fitting results between Chl-a and each environment factors

Season	Response variable	Explanatory variable	Edf	F	p	Dev. expl.	R ²
Spring	Chla	TP	0	0	0.839	30.60%	0.284
		TN	2.29	3.26	< 0.001***		
		AT	0	0	0.564		
		MWS	0	0	0.477		
Summer	Chla	TP	0	0	0.69	49.10%	0.48
		TN	0.99	7.64	< 0.001***		
		AT	0.69	0.25	0.0758		
		MWS	0	0	0.583		
Winter	Chla	TP	0.74	0.32	0.048*	67.60%	0.642
		TN	3.97	10.21	< 0.001***		
		AT	0.91	1.18	< 0.001***		
		MWS	1.52	0.44	0.064		

4. Discussion

Studies conducted on single-lake are sometimes criticized for their low generalizability, however, they often provide vital information about mechanistic pathways which are usually hidden in extensive multi-lake analysis. The study conducted here on Erhai Lake is used as an example of shallow and nutrient-enriched lakes which are being affected by climate change. This study identifies the patterns, especially the non-linear reactions of chlorophyll-a to temperature and wind forcing, pointing out the mechanisms that are important for managing lakes on a large scale.

4.1 Climatic modulation of eutrophication indicators

Erhai Lake serves as the major source of drinking water supply to Daly City. It has experienced significant algal blooms over the past 30 years, which may be attributed to serious eutrophication and deteriorating water quality (R. Wang et al., 2012; Lin et al., 2021). Nitrogen runoff from nearby farming operations

began around 1988, which may have contributed to the early stages of Erhai Lake's eutrophication process. The rise in urbanization, combined with human activities such as agriculture, construction, and tourism, has significantly influenced water quality of Erhai Lake (Xiao and Shen, 2019). These studies show that climatic variability, especially the changes in air temperature and wind speed, and nutrient concentrations significantly impacted the dynamics of chlorophyll-a (Chl-a) in Erhai Lake. Even at the constant nutrient concentrations, significant interannual variations in Chl-a were observed during the study period. This suggests that climatic factors may influence the eutrophication indicators in nutrient-enriched environments. Similar relationships between phytoplankton biomass and climate change have been demonstrated in both regional and multi-lake studies (Rigosi et al., 2015; Ho et al., 2019; Piccolroaz et al., 2020).

Rather than studying direct causative mechanisms, our study focused on statistical relationships. Wind speed may be related with vertical mixing, sediment resuspension, and the spatial redistribution of algal biomass, but increase in air temperatures may also promote phytoplankton growth by increasing metabolic rates, extend the growing season, and promote water-column stability (Wang et al., 2021; Zou et al., 2021). With significant climatic forcing, these interrelated processes make it more difficult to evaluate eutrophication measures.

4.2 Climate change-nutrient–Chla relationships

The very low interannual variability of TN and TP in comparison to Chla indicates that the observed bloom dynamics in Erhai Lake cannot be entirely explained by nutrient concentrations alone. Substantial nutrient dispersion suggests that same nutrient concentrations may result in varied phytoplankton responses under various climatic conditions, despite the clear positive relationships between nutrients and Chla. Similar results have been documented in earlier research emphasizing context-dependent and nonlinear nutrient–Chla correlations (Li et al., 2017; Li et al., 2019; Filazzola et al., 2020).

Over the past three decades, there has been a twofold increase in TN concentrations in Erhai Lake. This increase was prominent from 1988 to 2006 but stabilized in subsequent years. During the 2001–2006 period, a slight decline in TN concentrations and an increase in NH_4^+ levels could be linked to denitrification processes influenced by elevated AT over the lake (Kohler et al., 2005). It is possible that increasing AT leads to increasing WT, leading to increased microbial metabolism, which in turn leads to greater mineralization and TP sediment release. TP concentrations significantly fluctuated over the years. TP concentrations increased after 1996 and peaked in 2003 at 0.33 mg L^{-1} . Similarly, Chla concentrations reached highest in 2003 at $23 \text{ } \mu\text{g L}^{-1}$. AT's showed positive relationship with TP concentrations with a decrease during winters (Table 1). Hu et al. (2002) reported a 74% increase in P release during winters in Chaohu Lake. High ATs accelerate the mineralization of organic matter in lake sediments, releasing additional bioavailable nutrients into the water column (Gudas et al., 2010), which may also result in increased sediment P release. Algal blooms due to high AT also contribute to the release of organic P through organic matter decomposition (Jin and Tu, 2006). The relationship between climatic factors, nutrient concentrations, and Chla can vary across different lakes. For example, Dong et

al. (2018) revealed strong correlations between Chla and TP in Lake Fuxian, AT and TN in Lake Erhai, and AT, TP, and TN in Lake Dianchi in China. These results also align with our findings, where Chla showed significant correlations with TN in spring, summer, and winter, while AT was notably related to Chla in winters (Table 2). Variations in lake ecosystems may be corroborated with the differences in species composition and their tolerance to environmental factors (Walters et al., 2013; Rigosi et al., 2014). Between 1990 and 2000, *Cyanobacteria* sp. dominated, followed by a shift to *Dolichospermum* sp. from 1996 to 2006, and later, *Microcystis* sp. dominated in 2010, which might have contributed significantly to algal blooms in Erhai Lake (Dong et al., 2014; Dong et al., 2018). Our study also confirms that the increase in Chla concentration from an oligotrophic state to a hypertrophic state is related to high TN and TP concentrations (Fig. 5).

Wind speed (WS) appeared to be an important regulator of Chl-a variability due to nonlinear associations compatible with physical mixing and transport processes in shallow lakes. As extremely low or high WS may prevent biomass growth through stagnation or excessive mixing, moderate wind conditions may improve nutrient redistribution and keep phytoplankton in the photic zone (Tang et al., 2020; Jalil et al., 2021). Both experimental and observational research have documented similar wind-mediated effects on phytoplankton dispersal and bloom growth (Wang et al., 2021).

Wind speed (WS) exhibited a declining trend over the observed period, with an average value of 0.1 m s^{-1} (Fig. 2b). These impacts likely interact with internal sedimentation and nutrient cycling processes. The simultaneous increase in air temperature and decrease in wind speed can synergistically promote water column stability, increase internal nutrient loading and thereby increase Chl-a concentrations (Deng et al., 2018; Zhang et al., 2022)). Reduced WS potentially led to water column stability, emerging as a significant factor in the enhanced release of total phosphorus (TP) from sediments into the lake (Biddanda et al., 2018). The correlation between decreased WS and increased concentrations of dissolved TP and Chla aligns with findings in Taihu Lake (Deng et al., 2018). Lower WS conditions in Erhai Lake bring floating *cyanobacteria* closer to the surface, seeking sunlight, thereby causing algae to appear at the lake's surface during summer and winter seasons due to the low WS (Wang et al., 2021).

Strong correlation between Chl-a and COD in current study illustrates how algal biomass contributes to the buildup of organic matter in eutrophic lakes. Other lake systems have exhibited a similar relationship between organic matter indices and phytoplankton dynamics (Lin et al., 2021; H. Wang et al., 2020). Organic matter determination in lake ecosystems often depends on COD and COD_{mn} analyses. Like other nutrients, COD_{mn} concentrations also fluctuated due to seasonal variations and remained highest between 2000 and 2006 before experiencing a subsequent decline. Chen et al. (2020) highlighted regional differences, with higher COD observed in the north and west, and higher TN and TP in the southern and western parts of Erhai Lake, potentially due to nutrient runoff from agricultural activities. The increased TN and TP concentrations promoted abundant algal growth (Chen et al., 2020), contributing to the low (1.5 m) Secchi depth (SD) of Erhai Lake, particularly noticeable in 2003 (Fig. 4). A distinct trend between SD and Chla was observed over the 30-year monitoring period: before 2002–2003, SD was higher and Chla lower, but after 2003, SD significantly decreased as Chla increased (Fig. 4).

However, COD should be viewed as a reaction indicator rather than a causative factor in eutrophication processes because it partially represents organic matter generated from phytoplankton rather than an autonomous driver.

Cyclic variations in AT and WS observed in this study show that these climatic factors affect phytoplankton dynamics through separate processes that function on various temporal periods. As seen in other warming lake systems, seasonal warming, particularly increases in winter temperatures, may shorten the period of adverse growth circumstances and help initiate blooms earlier (Frank et al., 2023; Ligorini et al., 2023). These impacts, however, probably interact with internal sedimentation and nutrient cycling processes that were not specifically addressed here.

The cyclical variations in climate and increased nutrient concentrations have exacerbated water quality concerns in Erhai Lake over the past three decades. Studies on the water quality of Erhai Lake have indicated a shift from Class I-II in the 1980s to Class III presently, based on China's Environmental Quality Standards for Surface Water (GB3838-2002) (Wang et al., 2015; Chen et al., 2021). From 1992 to 1998, Erhai Lake maintained a Class II water quality, but after 1999, it deteriorated to Class III (Wang et al., 2015). It is speculated that the water quality of Erhai Lake might further deteriorate to Class IV and Class V due to the consistent increase in algal blooms (Chen et al., 2021). Continuous monitoring of climate variations and nutrient concentrations, which contribute to the rising algal blooms in Erhai Lake, is essential. The current study provides valuable scientific insights into the impacts of cyclical climate variations and nutrient concentrations on Chla, offering crucial information for sustainable lake management and the preservation of water quality within acceptable limits according to environmental standards.

4.3 Implications for indicator-based lake assessment

From an indicator-based perspective, our findings demonstrate that the sensitivity of Chla to nutrient concentrations can be greatly affected by climatic variations. Warming lake surface temperatures may increase Chla concentrations without corresponding increases in nutrient inputs, and wind-driven mixing can either promote or decrease bloom expression. Similar climate-driven variations in indicator behavior have been reported for a range of lake types (Adu-Prah et al., 2019; Woolway et al., 2021).

Our findings also show the challenges of depending solely on static nutrient thresholds for eutrophication assessment and highlight the importance of dynamic interpretation of ecological indicators that consider climatic context. Early warning skills may be enhanced by including climatic variables into indicator-based evaluation frameworks, and bloom episodes may be less likely to be wrongly attributed to nutrient loading alone.

4.4 Broader relevance of the study

This study focused on Erhai Lake; however, it is also applicable to several shallow and polymictic lakes with ongoing nutrient enrichment and rising climatic variability. Comprehensive single-lake studies offer crucial insight into system-specific indicator responses (Johnson and Chess, 2006; Maas-Hebner et al.,

2015), while prior multi-lake analyses have shown broad patterns in interactions between climate, nutrient and phytoplankton (Wu et al., 2016; Thomas et al., 2018; Tasnim et al., 2021).

This single-lake study is useful in its capacity to clarify the broader use of eutrophication indicators reacting to long-term climate–nutrient interactions rather than from its geographic specificity. Such results can guide the use of indicators and lake management techniques outside of the research area when evaluated within a more comprehensive conceptual framework (Liang et al., 2020).

4.5 Challenges for sustainable water resource management

This study is practically relevant to the sustainable governance of drinking-water lakes in developing regions. Because Erhai Lake supplies water to Dali City, changes in Chla due to combined impacts of climate and nutrients result directly in risks for drinking-water treatment costs, public health, and the tourism-dependent local economy. Rather than relying solely on nutrient thresholds, integrating climatic context into water-quality monitoring would strengthen early-warning systems and support the kind of adaptive, evidence-based management mandatory under SDG 6. In a broader context, the interaction between agricultural nutrient runoff, urbanization, and climate warming reported in our study exhibits a common tension in developing regions between economic growth and environmental sustainability, highlighting the need for integrated land-water management policies that anticipate changes in water quality due to climatic influences rather than reacting to them after blooms occur.

4.6 Challenges for environmental monitoring and assessment

This study highlights the importance of comprehensive, long-term monitoring for evaluating climate–nutrient–chla relationships and comes up with the following important monitoring limitations: (1) Seasonal sampling only is not sufficient to demonstrate bloom dynamics, rather, monthly monitoring provides more reliable assessment; (2) Comprehensive assessment requires multiple indicators (Chla, TN, TP, SD); (3) Monitoring programs should incorporate meteorological parameters; and (4) The observed cyclic patterns suggest that monitoring programs should span at least 10–15 years to establish baseline trends. These results can help design monitoring programs for additional highland lakes, especially in developing areas with little monitoring resources.

4.7 Limitations and future research

Due to the observational character of the dataset and the correlative structure of the GAM analysis, the causal inference was not possible. Moreover, the water-column thermal dynamics might not be well understood by using air temperature as a substitute for thermal forcing. Further, the absences of data after 2017 limited the evaluation of recent trends in climate forcing and eutrophication indicators.

Future research must focus on combining long-term monitoring with experimental and process-based methods for better understanding of the mechanisms for the observed relationships between climate,

nutrients, and phytoplankton. Addition of biological and biogeochemical indicators may enhance our understanding about eutrophication processes due to climate change.

Conclusions

The 30-year monitoring of variations in climate cycles and increasing nutrient concentrations have significantly contributed to the rise of algal blooms in Erhai Lake. Key findings of the study conclude that the average annual AT over Erhai Lake increased by 0.8 °C/decade with 4–6 years cycles, while WS decreased by 30%. The TN and TP concentrations showed significant increases during 2001 to 2006, which are attributed to agricultural and domestic activities around Erhai Lake. GAM-based assessment identified TN as the dominant nutrient driver, with climate effects most pronounced in winter. High Chla concentrations showed that this TN influx further exacerbated algal blooms. The complex climate-nutrient interactions had a profound impact on the water quality of Erhai Lake. The water quality deteriorated from Class II (1980s to 1990s) to Class III after 2000, highlighting the importance of sustained water quality monitoring. Absence of appropriate measures may further deteriorate water quality to Class IV and V. This study determines that effective environmental monitoring and assessment entails: (1) long-term systematic data collection; (2) integration of meteorological and physicochemical assessments; (3) utilizing advanced analytical techniques (GAM) to identify nonlinear relationships; and (4) converting monitoring results into management decisions. By promoting climate-informed water quality management, supporting SDG 6, the analytical framework developed by this study can direct monitoring programs in other highland lakes facing similar stresses.

Declarations

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Declaration of generative AI and AI-assisted technologies

During the preparation of this work the author(s) used Quillbot service to improve the language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration on conflict of interest

The authors declare no conflict of interest.

Clinical trial number

Not applicable

Ethics and Consent to Participate declarations

Not applicable

Consent to Publish declaration

Not applicable

Declaration on data availability

Data supporting this study may be made available in the supplementary material or upon reasonable request from the corresponding author

Author Contribution

All authors contributed to the study conception and design. Conceptualization of research topic and research framework, overall project coordination and schedule management, drafting of manuscripts especially the introduction and the materials and methods sections was done by L.Z. Literature search, organization, and data analysis, questionnaire designing and experimental protocols and drafting of results and discussion section was done by C.T. Descriptive statistics, and charts and graphs were created by R.Y. and Y.L. provided insights and engaged in discussions regarding the paper. Z.H. revised and polished the language of the entire manuscript. All authors read and approved the final manuscript.

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Figures

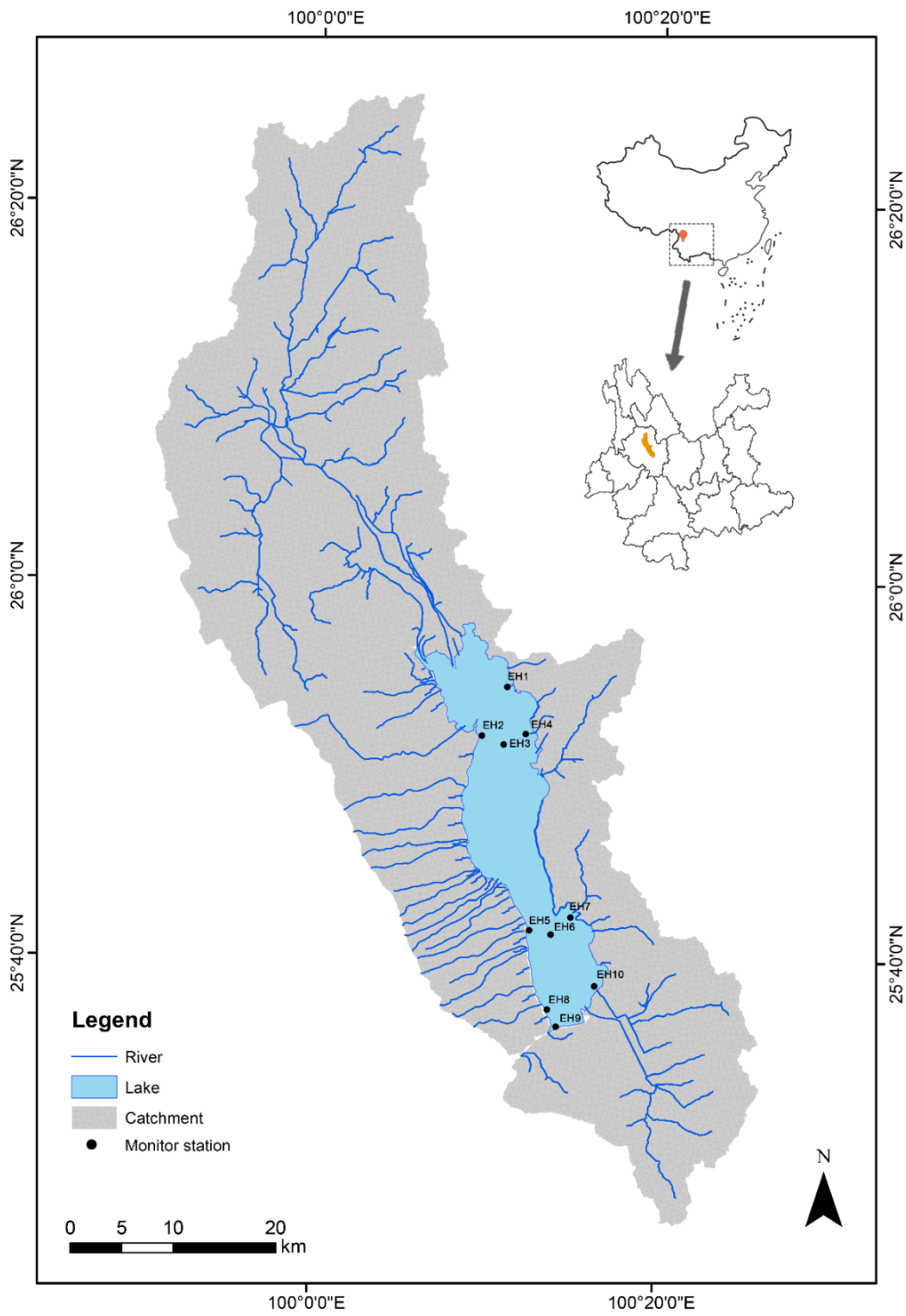
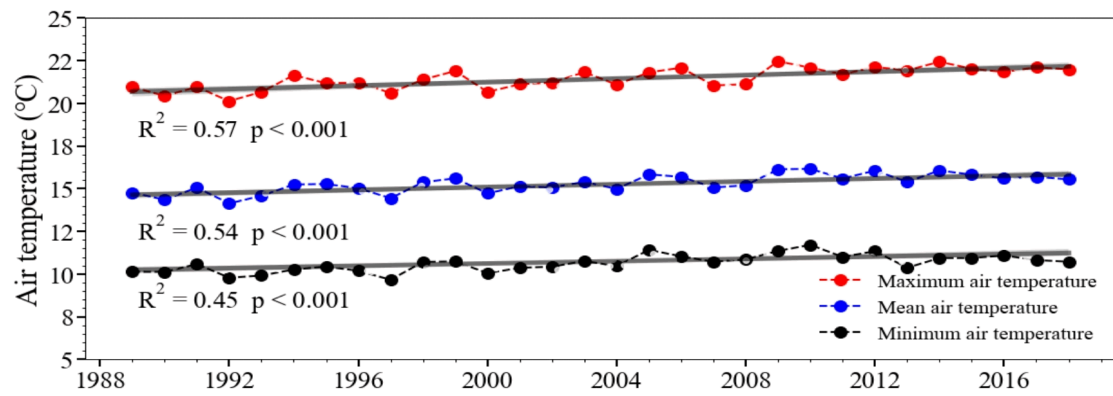
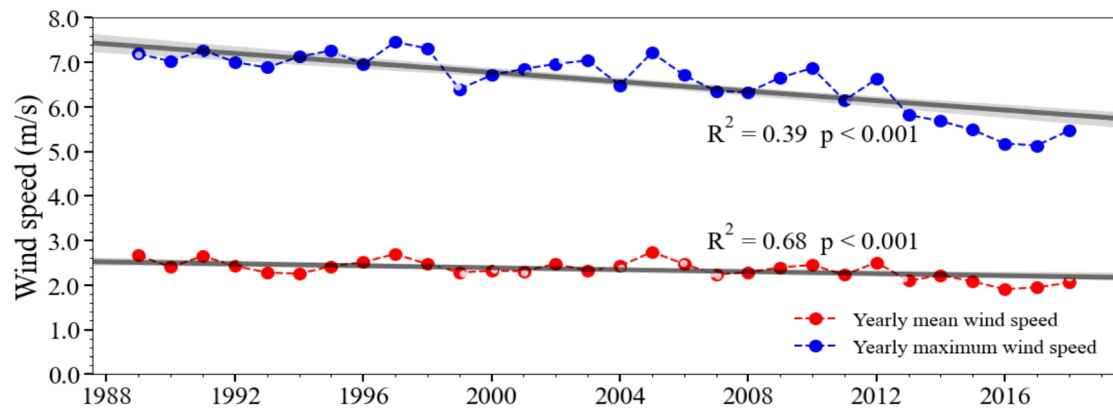


Figure 1

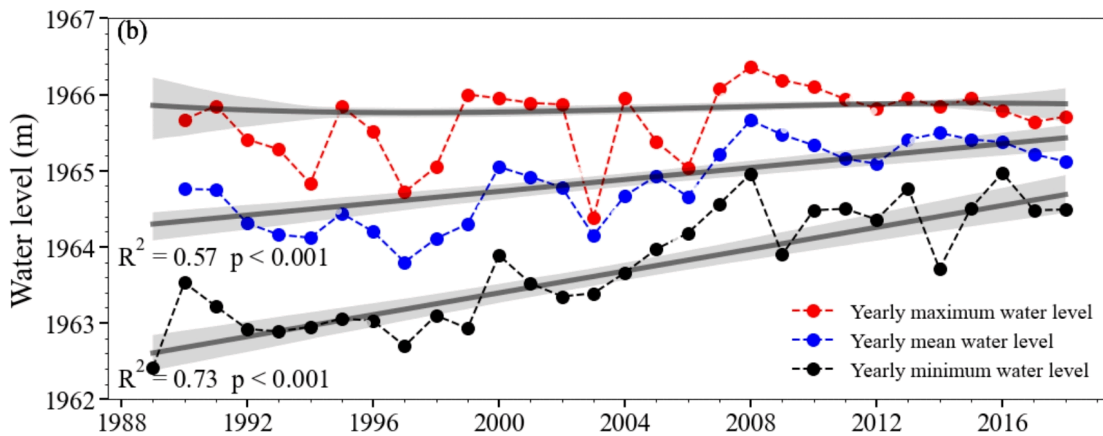
Study location of Erhai Lake



a



b



c

Figure 2

Trend of air temperature (a), wind speed (b) and water level (c)

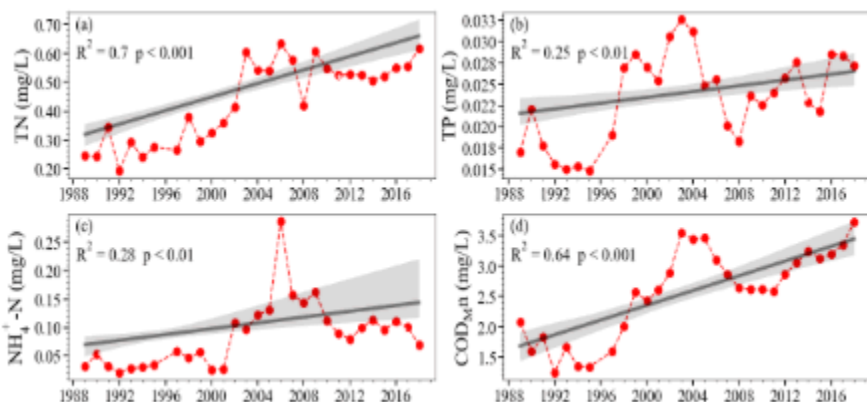


Figure 3

Trend of water quality

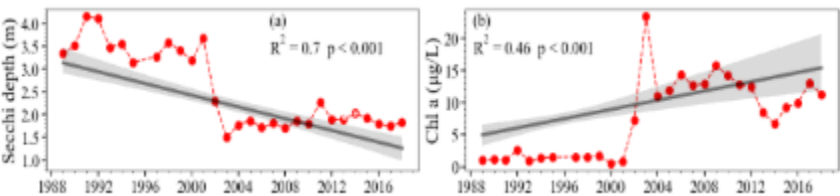


Figure 4

Trend of Secchi depth and Chla

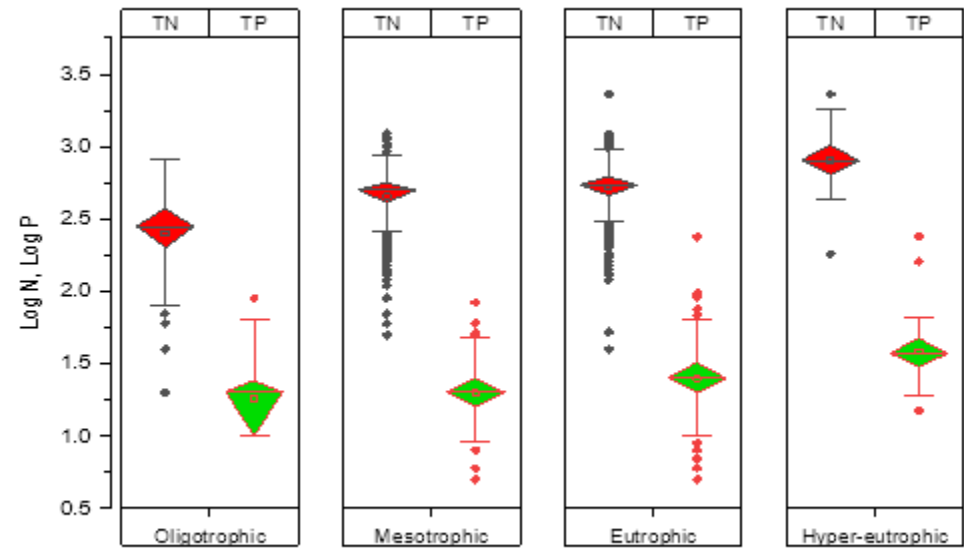


Figure 5

Log concentrations of TN and TP in four trophic stages

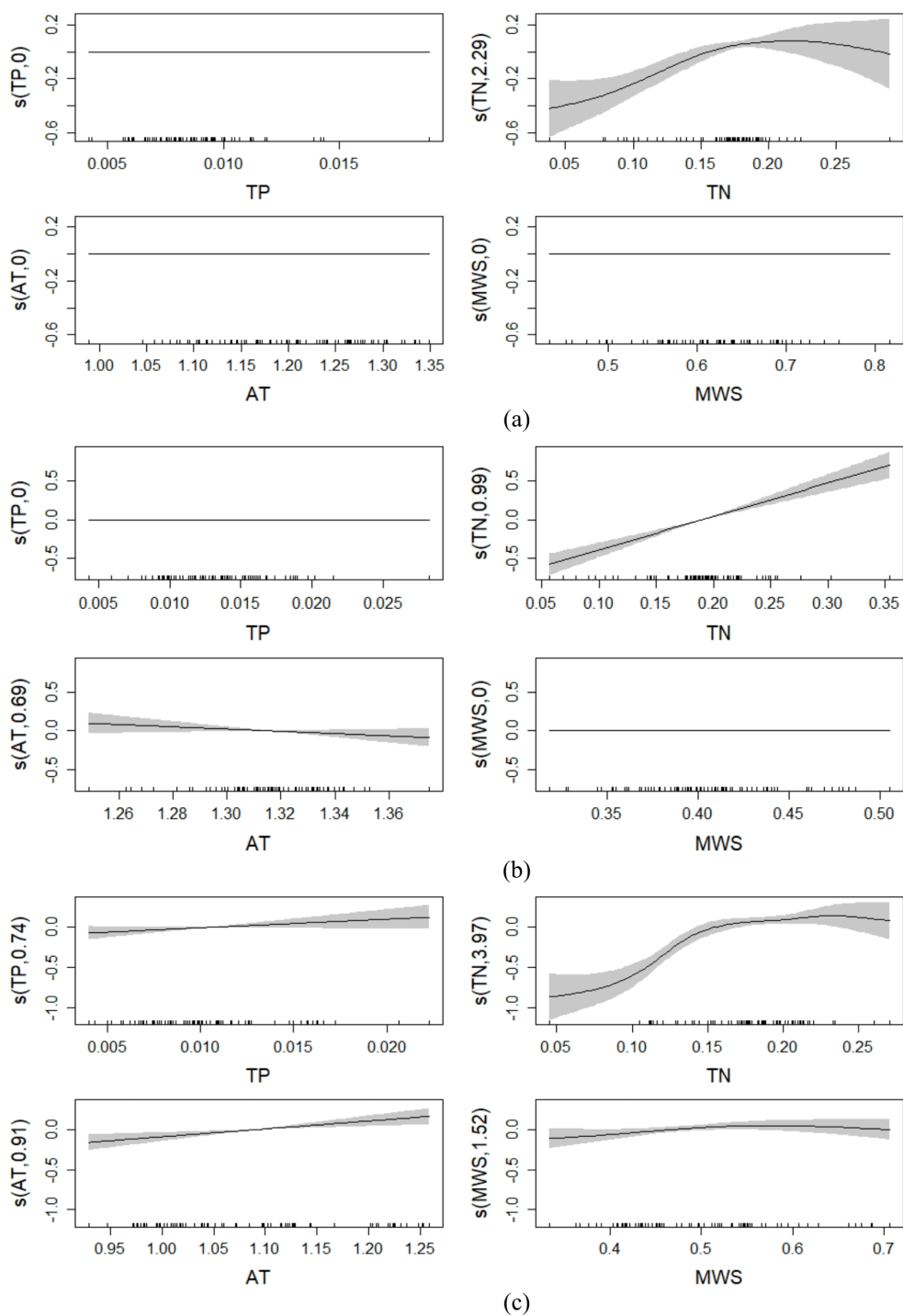


Figure 6

The response of chlorophyll a (Chla) to explanatory variables in spring (a), summer (b) and winter (c). The grey shadow denotes 95% confidence interval of the estimation, and the number in vertical axis title represents the estimated degree of freedom used to fit each variable.