Science of the Total Environment xxx (xxxx) 177247

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com

Looking beyond the surface: Understanding the role of multiple stressors on the eutrophication status of the Albufera Lake (Valencia, Spain)

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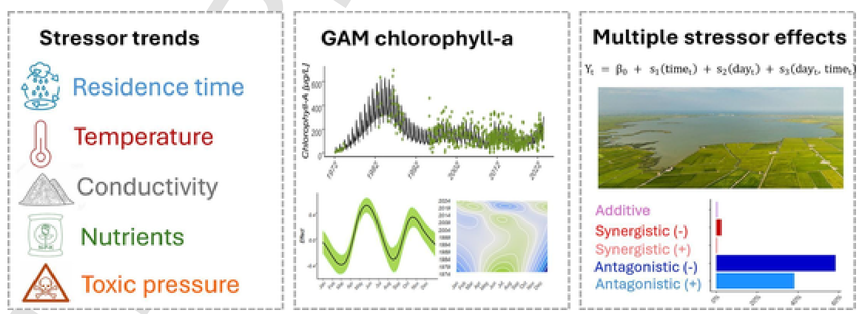
HIGHLIGHTS

- We compiled a 50-year data series for the main stressors affecting the Albufera Lake.
- GAMs were applied to model single and multiple stressor effects on chlorophyll-a.
- Temperature, water scarcity, and nitrate concentrations affect chlorophyll-a.
- Multiple stressor effects were found to be highly dynamic and mostly antagonistic.
- Specific measures to improve the ecological status of the Albufera Lake are provided.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Sergi Sabater

Keywords:
Eutrophication
Multiple stressors
Climate change
Wetlands
Ecosystem management

ABSTRACT

Aquatic ecosystems face significant impacts from human-related stressors, demanding a deep understanding of their dynamics and interactions for effective management and restoration. The Albufera Lake (Valencia, Spain) presents a complex scenario of multiple interacting stressors affecting its eutrophic status. In this study, we compiled a 50-year dataset and used Generalized Additive Models (GAMs) to analyse the dynamics of the main stressors affecting the ecological status of the Albufera Lake. Then, we assessed their individual and combined effects on eutrophication using chlorophyll-a concentration as a proxy and provided recommendations to enhance water quality. Overall, we found a decrease in annual water inflow and a clear effect of rice cultivation on the seasonal patterns of the Lake's residence time. Our analysis also shows an increase of average water temperature of 2 °C for the last 50 years, and an increase in the frequency and severity of heat waves. In contrast, we found a slightly negative long-term trend in conductivity, despite the occurrence of seasonal peaks in summer. Regarding nutrients, we identified a clear reduction of total phosphorus (from 1.08 mg/L in 1987 to 0.20 mg/L in 2022), while nitrate concentrations have been rather stable. Our results also point at an increase of toxic pressure exerted by organic and inorganic contaminants during the last years, with seasonal toxicity peaks occurring during rice field drainage periods. The main stressors affecting the chlorophyll-a levels were found to be temperature, water scarcity, and nitrate concentration as well as the interactions between temperature and conductivity, conductivity and nitrate, conductivity and water scarcity, and nitrate and total phosphorus. We found that stressor interactions are highly dynamic and result in synergistic and antagonistic effects that vary according to different stressor levels. Finally, our GAM framework points to two potential scenarios: increasing freshwater inflows or deregulat-

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https://doi.org/10.1016/j.scitotenv.2024.177247
Received 1 August 2024; Received in revised form 25 October 2024; Accepted 25 October 2024
0048-9697/© 20XX

ing hydrology to allow seawater exchange, which are key for improving the ecological status of the Albufera Lake in the short-term.

1. Introduction

The exponential growth of the human population and its related activities profoundly contribute to change the structure of aquatic ecosystems, setting in motion gradual or sudden shifts (Scheffer et al., 2009; Halpern et al., 2019). These changes arise from environmental pressures, often referred to as stressors, which encompass a wide range of human activities impacting biogeochemical, hydrological, and ecological processes at local and global scales (Vinebrooke et al., 2004; Folke et al., 2004; Lange et al., 2018). The effects of multiple stressors can vary, ranging from situations where a single stressor dominates to more complex scenarios where simultaneous consideration of two or more stressors becomes necessary to explain observed ecological responses (Côté et al., 2016; Crain et al., 2008; Gutiérrez-Cánovas et al., 2022). In such cases, the combined effects of stressors can exhibit either additive characteristics, where the combined effect is equal to the sum of individual stressor effects, or interactive characteristics, where the combined effect is lower than (antagonism) or greater than (synergism) the anticipated additive response (Piggott et al., 2015). Understanding the temporal dynamics of multiple stressors and the ways in which they interact is key to providing guidance to managers involved in conservation and restoration of aquatic ecosystems (Côté et al., 2016).

Among the list of stressors affecting freshwater ecosystems, nutrient contamination has been recognized as one of the most threatening ones (Birk et al., 2020). Nutrient enrichment explains about 35 % of the variance in the ecological status of European surface waters (Lemm et al., 2020). Excessive nutrient loads result in an alarming increase of phytoplankton biomass, producing the eutrophication of aquatic ecosystems and reducing their biodiversity (Donohue et al., 2009; Polazzo et al., 2022a). However, nutrient contamination is not the only stressor that contributes to eutrophication, particularly under Mediterranean conditions. For example, water scarcity, due to climate change and water abstraction, results in increasing residence times of lakes and coastal wetlands as well as reduced dilution of other contaminants (Arenas-Sánchez et al., 2016). Similarly, increasing water temperatures and the higher prevalence and magnitude of heat waves foster changes in the structure of primary producer communities and an overall increase of phytoplankton density (Markensten et al., 2010; Pulina et al., 2020). On the other hand, metals and other synthetic chemicals (e.g. pesticides, pharmaceuticals, industrial compounds) can result in toxic effects on phytoplankton grazers, thus contributing to eutrophication (Vilas-Boas et al., 2021).

The Albufera Lake (Valencia, Spain) serves as a prime example of the intricate interplay between multiple stressors affecting the ecological status of surface water ecosystems. This shallow, polymictic coastal lake is characterized by a hypertrophic status, with chlorophyll-a concentrations that currently range between 18 and 331 μg/L (IZONASH, 2023). It is one of the most studied coastal wetlands in the Mediterranean region (Martínez-Megías and Rico, 2022), as it confronts numerous challenges, including hydrological disruptions resulting from the large rice farming area that occupies the surroundings of the lake, physicochemical changes induced by climate change, nutrient inputs from diverse sources, salinity fluctuations, and toxicological hazards associated to the extensive use of agricultural pesticides, legacy metal contamination and down-the-drain chemicals (Villena & Romo, 2003; Martín et al., 2020, Calvo et al., 2021; Soria et al., 2021a; Soria et al., 2021b, Martínez-Megías et al., 2024). Numerous objectives and interventions have been proposed with the aim of improving lake's ecological status, with limited success so far (Martín et al., 2020). In line with the Water Framework Directive (WFD) and based on the results of the ECOFRAME project (Moss et al., 2003), key targets have been established to reach an average chlorophyll-a concentration of 30 μg/L by 2027 and to reduce total phosphorus (TP) below 50 μg/L (CHJ, 2018). Achieving these targets requires a thorough understanding of how the different variables affecting the eutrophic status of the lake are interlinked and which management actions should be prioritized.

Most studies assessing anthropogenic impacts on the Albufera Lake, and other Mediterranean wetlands, have traditionally focused on isolated stressors; while investigations that evaluate the occurrence of multiple stressors and their cumulative impacts are notably scarce (Martínez-Megías and Rico, 2022). Generalized Additive Models (GAMs) provide a powerful regression framework that extends traditional linear models by allowing for non-linear relationships between predictors and response variables (Hastie and Tibshirani, 1987; Wood, 2017). They have been applied to the analysis of ecological time-series, harnessing their ability to capture non-linear relationships and temporal trends in data (Simpson, 2018). However, the application of GAMs in the context of multiple stressors—where there is a need to understand how concurrent, interrelated stress factors dynamically interact and impact ecosystem function and structure—remains less explored. In this context, a key advantage of GAMs lies in their use of tensor products smooths, which enable evaluating complex interactions between multiple variables in a flexible, non-parametric framework, thus allowing to capture the effects of multidimensional stressor interactions over long time periods (Wood, 2006).

In this study we applied a GAM approach to understand the role of multiple stressors affecting the ecological status of the Albufera Lake and to define ecosystem restoration measures that are key to reverse its eutrophic status. The specific objectives of this study were: (1) to analyse and model the dynamics of each of the stressors that may have potentially contributed to the eutrophication of the Albufera Lake during the last 50 years; (2) to assess the single and combined effects of these stressors on the ecological status of the Albufera Lake using the concentration of chlorophyll-a as a proxy for eutrophication; and (3) to define what are the variable combinations and the management measures that should be implemented to reach the chlorophyll-a concentration target set by the WFD. By doing this, we provide valuable insights into the complex dynamics of multiple stressors that are affecting the ecological status of an hypereutrophic lake, which can be used to inform ecosystem management and restoration for other wetland ecosystems in the Mediterranean region.

2. Material and methods

2.1. Stressors data series

A database was constructed for various hydrological and water quality parameters that reflect the main anthropogenic pressures that have potentially impacted the ecological status of the Albufera Lake over the last 50 years (1973–2023). These parameters encompass: (1) water residence time, as an indicator of water scarcity; (2) water temperature, to assess the influence of global warming; (3) water conductivity, as a proxy for salinization; (4) nitrate and total phosphorus (TP) concentrations, as key nutrients; and (5) the multi-substance Potentially Affected Fraction (msPAF), as a mixture toxicity indicator for aquatic organisms calculated with measured concentrations of metals and organic contaminants (e.g. PCBs, pesticides; see e.g. Martínez-Megías et al., 2024). A detailed description of the data source and calculations used to build the database is provided in the Supplementary Information file I, while the database itself is provided in the Supplementary Information file II.

2.2. Stressor dynamics

To analyse the time-related patterns of both, the stressor data series and the response variable (i.e., chlorophyll-a) we fitted a GAM that includes (1) a long-term trend to assess changes over the 50-year period; (2) a seasonal component that uses the day of the year with a cyclic spline to identify intra-annual variation; and (3) a tensor product that combines these two to explore how seasonal effects may have shifted over time. The model reads:

$$Y_t = \beta_0 + s_1\left(\text{time}_t\right) + s_2\left(\text{day}_t\right) + s_3\left(\text{day}_t, \text{time}_t\right) \quad (1)$$

Where Y_t is the response variable (i.e., chlorophyll-a) at time "t", β_0 is the intercept, $s_1(\text{time}_t)$ is the term capturing the effect of time over the data series (long-term trend), $s_2(\text{day}_t)$ is the term capturing the effect of the specific day of the year on the response variable (seasonal variation), and $s_3(\text{day}_t, \text{time}_t)$ is the interaction term in the form of a tensor product that captures the combined effect of day (seasonal variation) and time (long-term trend) on Y_t. The spline used for $s_2(\text{day}_t)$ forces the data to start and end similarly, which is typically appropriate for modelling seasonal patterns.

The GAM time series modelling for this study was conducted using the *'mgcv'* package in R (Wood, 2017; R Core Team, 2024), which provides a flexible framework for fitting and evaluating GAMs. To identify the optimal model for each stressor, we systematically evaluated multiple combinations of link functions and families, chosen according to the conditional distribution of the response variable. For each model configuration, the appropriate number of knots was determined using the *gam.check* function from the *'mgcv'* package. Model selection was guided primarily by the Akaike Information Criterion (AIC), with additional validation through residual analysis to ensure consistent error distribution. We first fitted the models using Maximum Likelihood (ML) estimation and then refitted the best-fitting model using Restricted Maximum Likelihood (REML), following the recommendations of Simpson (2018). All observations were weighted based on the time difference (in days) to the nearest neighbouring observation and the sample interval. The need for explicit autocorrelation structures was evaluated using the Autocorrelation Function (ACF) and the partial Autocorrelation Function (pACF) indexes. Statistical significance of the model components was determined when the calculated p-values were < 0.05.

Due to the limited length of the time series on residence time, assessing its long-term trend was deemed unfeasible. Given the existence of a single annual inflow value for each year, the daily residence time dataset was sampled by obtaining data for 40 d, which were then related to the total inflow for each corresponding year. Resampling the original dataset allowed for the quantitative integration of the total inflow variable into the analysis. Thus, the daily residence time of these 40 d was modelled with a seasonal component, included as a cyclic spline, and the total annual inflow as a parametric component.

Temperature modelling involved two GAMs. The first one established the relationship between the weekly rolling mean air temperature provided by IVIA (Instituto Valenciano de Ciencias Agrarias) at the Benifaió meteorological station and the lake's water temperature. While the second one analysed the temporal components of these predictions as described above. The first temperature model was also used to identify heatwaves (HW) by adopting the World Meteorological Association's definition: "a sequence of five or more consecutive days of prolonged heat, where the daily maximum temperature exceeds the average maximum temperature by 5°C or more". Thus, predictions that exceeded the annual mean maximum temperature for > 5 d were flagged as heatwaves.

In all cases, partial effects were plotted for each model component using the *´ggplot2´* (Wickham, 2016) package in R (R Core Team, 2024), illustrating the relationship of a single predictor variable (i.e., long-term trend, seasonal component, or tensor product) on the response variable (i.e., stressor data series), while holding all other predictor variables constant. For each smooth, both pointwise and simultaneous confidence intervals were calculated using the *confint* function from the *´stats´* R package (R Core Team, 2024), providing comprehensive uncertainty estimates for the model predictions. These confidence intervals were also included in the partial effects plots to visually represent the uncertainty around the predicted effects. Partial effects derived from the cyclic spline elucidate the intensity of seasonal patterns, whereas trend's partial effects disclose long term-changes (and change speed) in the response variable. This distinction is crucial, as it clarifies whether observed changes are part of a natural cycle or indicative of a broader trend. By also examining effects associated to the tensor product that combines these two components, we assessed how seasonal patterns change in the context of long-term trends, thus gaining a better understanding of the variable's evolution during the last 50 years.

2.3. Multiple stressor effects on chlorophyll-a

To assess the impact of the evaluated stressors on chlorophyll-a, a GAM model that used residence time, water temperature, water conductivity, nitrate concentration, TP and the chronic msPAF as predictors was built. This model extended the chlorophyll-a temporal analysis by incorporating the selected stressors along with the seasonal component, offering a comprehensive understanding of the factors affecting chlorophyll-a concentrations and their interactive effect. The model selection process began with a base formula that included all individual smoothed terms for the stressors and seasonality. We iteratively added interactions as pairs of variable using the *ti* function from the *´mgcv´* package to identify combinations that improved model fit, evaluated using the AIC. This approach enabled us to determine which interactions enhanced model performance without overfitting. All binary interactions were examined except those involving the seasonal component, to avoid complications related to the interactions of stressors and time. During this process, various distribution families were tested, ultimately selecting the one that best captured the distributional characteristics of the data by checking its AIC value and the residuals distribution. Once the best model was identified, we applied an additional simplification process, testing whether removing each interaction would lead to further improvement in terms of the AIC. The final number of knots for the smooth terms was determined using the *gam.check* function of the *´mgcv´* package.

Additionally, we computed partial effects from all variables and tensor products included in the model to identify stressor interactions. Then, we classified the binary stressor interactions into additive, antagonistic, or synergistic by comparing the sign and magnitude of the tensor product estimate (E), with the individual estimates of the variables involved (see Piggott et al., 2015 and Fig. 1). Additive effects are a straightforward sum of individual effects, showing double-positive ($+1 + 1 = 2$), double-negative ($-1 + -1 = -2$) or opposing effects ($-1 + 1 = 0$) depending on the sign of the effects of the individual stressors. Positive antagonistic interactions ($+$A) occur when the combined effect is less than the additive prediction but still positive (e.g., $+1 + 1 = 0 < E < 2$), while negative antagonistic interactions ($-$A) occur when the combined effect is less negative than expected (e.g., $-1 - 1 = -2 < E < 0$). Synergistic interactions are positive ($+$S) if the combined effect exceeds the sum of individual effects (e.g., $+1 + 1 = E > 2$) or negative ($-$S) if the combined effect is more negative than the sum (e.g., $-1 - 1 = E < -2$).

Orr et al. (2024) highlight the critical role of null models in multiple stressor analyses to separate actual interactions from random noise. To do so, we built a chlorophyll-a null model with the same structure but using predictors randomly sampled from observed data, subtracting the null model's effect from each variable's effect. Given the variability of GAMs effects within variable ranges, effects smaller than 0.01 were assumed to be 0 to represent neutral interactions.

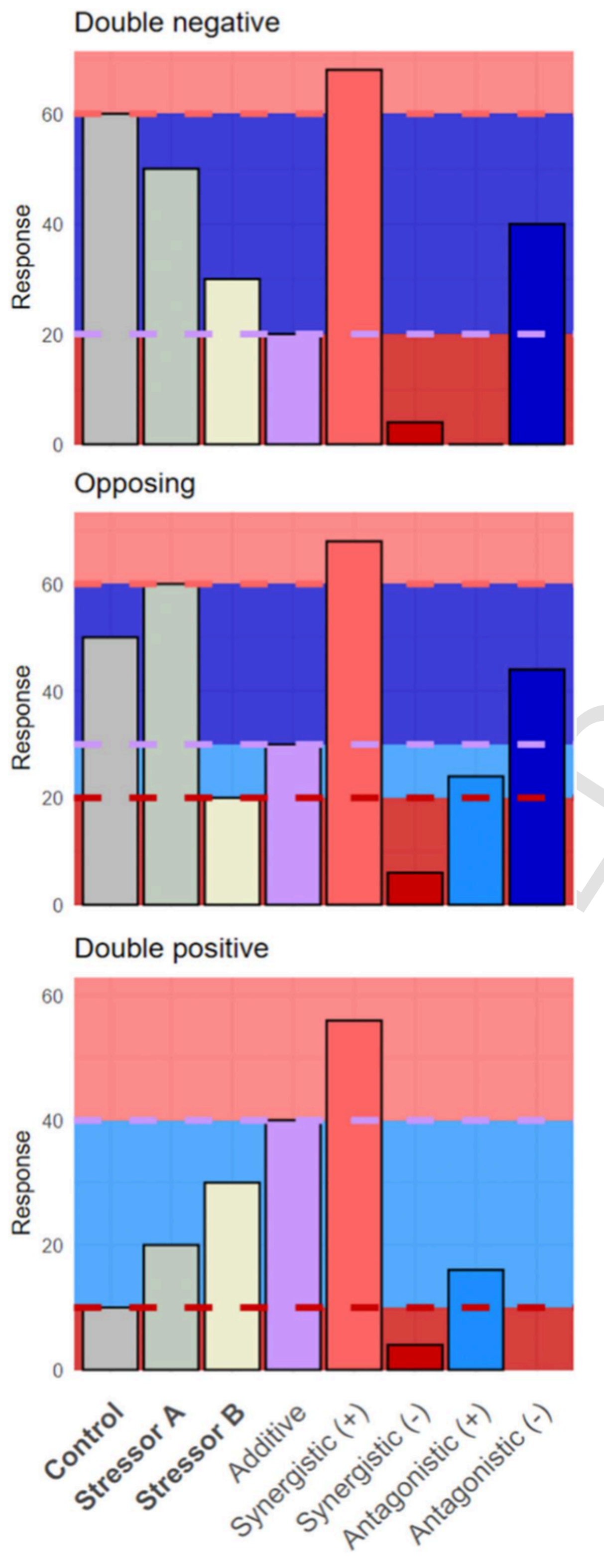

Fig. 1. Conceptual framework for the classification of multiple stressor effects based on Piggott et al. (2015). Our study includes a null model (control), the effect of variable A, the effect of variable B, and the interaction effect. Interaction effects are categorized as additive (AD), negative synergistic (—S), positive synergistic (+S), positive antagonistic (+A), and negative antagonistic (−A), as shown in the figure. These multiple stressor categories are determined

Fig. 1.—*continued*
by comparing A + B to the sum (AD) of the individual effects caused by stressor A and stressor B relative to the control (CT). The three plots illustrate the interaction effects resulting from three possible scenarios: (a) double-negative (both stressors result in negative effects on chlorophyll-a); (b) opposing (one stressor results in negative effects and the other in positive effects on chlorophyll-a); and (c) and double-positive (both stressors result in positive effects on chlorophyll-a).

To further address the uncertainty in the interaction effects, we applied posterior sampling using the *smooth_samples* function from the *´gratia´* package (Simpson, 2024) to generate multiple realizations of the smooth terms. This approach allowed us to assess how the classification of interaction types changed across samples, providing a more robust representation of the interaction surface. We then classified each region into one of the five interaction types described in Piggott et al. (2015), which are summarized in Fig. 1, and calculated the proportion of times each region was consistently classified in the same way across the posterior samples. Subsequently, with the aim of visualising the occurrence of each type of interaction, we created a grid of observed values for each pair of variables and categorized their interactions across their entire range. In this way, each combination of values for the two variables was associated with an "interaction type" and were represented in a heatmap using the ´ggplot2´ package (Wickham, 2016) in R (R Core Team, 2024). Only regions with >90 % consistency were confidently classified, while areas with higher uncertainty were represented with reduced opacity (*alpha* in R) to visually convey their lack of reliability. This method ensured that the final heatmaps do not only displayed the interaction effects but also accounted for the uncertainty in those effects, thereby providing a more nuanced interpretation of multiple stressor interactions.

2.4. Water quality management

To assess what are the management actions that should be achieved to reduce the chlorophyll-a concentration of the Albufera Lake and meet the WFD target of 30 μg/L, we generated a Monte Carlo sampling of 10,000 stressor combinations for each day of the year (i.e., a total of 3,650,000 simulations). The Monte Carlo sampling was created by sampling the stressors uniformly within the day-specific observed ranges. These ranges were determined from the stressor data series by selecting the minimum and maximum values recorded for each variable on each day, thus capturing the seasonal variability of environmental and water quality parameters. Chronic msPAF values were set to zero, to exclude stressor combinations that advocate for an increase of toxic pressure to reduce the chlorophyll-a concentration. Similarly, the maximum TP concentration was set to 50 μg/L, as this is the maximum value stipulated by the WFD. The combinations generated for each day were used as input to the chlorophyll-a GAM model, which predicted the associated chlorophyll-a concentrations. This dataset was then filtered to identify combinations of variables that resulted in predictions of chlorophyll-a below 30 μg/L. All possible combinations were then grouped into two groups using a k-means clustering approach based on Euclidean distances, which identified two main pathways (i.e., stressor combinations) to achieve the water quality targets set by the WFD. The k-means clustering was calculated using the *´stats´* package in R (R Core Team, 2024).

3. Results

3.1. Stressor dynamics

Given the distributional characteristics of the residence time variable, the best fitting model used a gamma family and the logarithm as the link function (Table S2). Within this model, we found a negative association of total yearly inflow with residence time, with larger inflows decreasing residence times in the lake (Fig. 2A and B), though this relationship was marginally significant (p-value <0.1). Thus, the years with lowest yearly water inflow (158 and 162 hm^3 in 2018 and 1994, respectively) are the ones that reach maximum yearly mean residence time (18 ± 15 and 17 ± 21 d; mean ± standard deviation). The seasonal component shows the marked influence of rice cultivation on the hydrology of the lake, with the longest residence times occurring during the winter-flooding (Fig. 2C). The shortest residence times occur between February and March when all rice fields are being emptied to prepare for sowing, and between August and September, when the rice fields are emptied for harvest. The months with the largest residence time are October and November (with averages of 30 ± 18 and 23 ± 15 d, respectively), and the shortest are August and February (3.2 ± 1.5 and 3.7 ± 1.7 d). The model accounts for 66 % of the deviance within the hydrological data subset (Table 1). Model diagnostic plots for water residence time are available in the Supporting Information (Fig. S1A).

In the case of water temperature, the Gaussian family with an identity link resulted in the best fitting models (Table S2). Temperature models show significant patterns in both the long-term and the seasonal dynamics, as well as their combined effects (Table 1). Water temperature temporal patterns revealed an upward long-term trend and a seasonal cycle that peaks towards the end of July - beginning of August (Fig. 3). Yearly mean water temperatures have increased from 18 ± 6 °C in 1972, to 20 ± 7 °C in 2022; while the highest yearly mean water temperature corresponds to 2021 (22 °C). Five observations exceeded 30 °C, 3 of which took place after 2020.

The tensor product heatmap reveals a shift in seasonal trends, with cooler winter temperatures and warmer summer temperatures observed in recent years compared to the 1970s. The final temperature model explained 98 % of deviance within the temperature predictions. Following the heatwave definition, the predictive temperature model

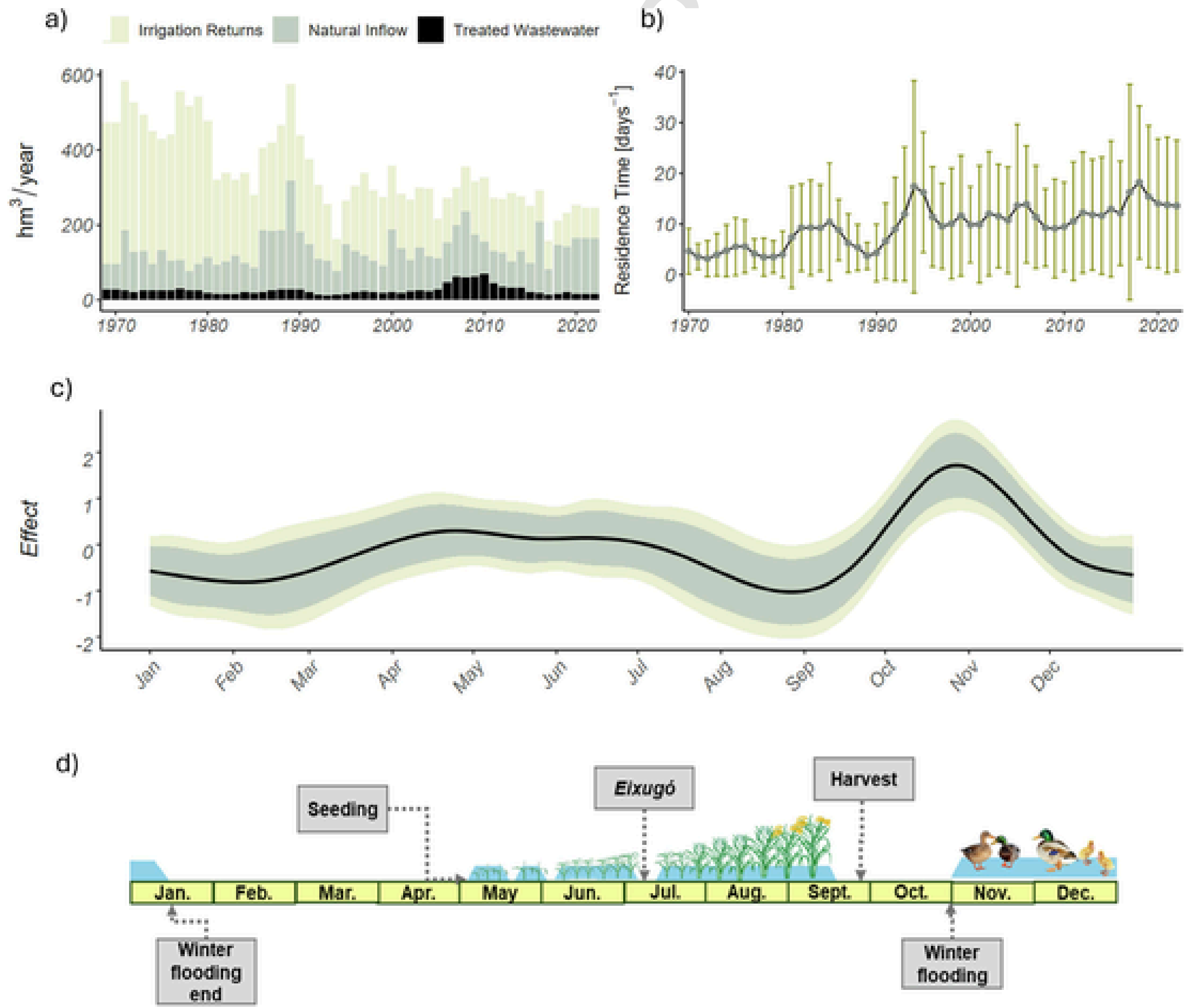

Fig. 2. Hydrological information: total inflow time-series (a), predicted yearly average residence time of the lake (b), seasonal component of the residence time GAM (c), and drawing showing the different phases of the rice growing period together with its seasonal flooding and emptying events (c). In the last figure, *Eixugó* refers to the long desiccation period (7 d) used to apply pesticides (insecticides, herbicides) during rice cultivation, while the previous shorter desiccation periods are used for the application of herbicides.

Table 1
Results of the Generalized Additive Models (GAMs) built to assess the temporal dynamics of residence time, temperature, conductivity, nitrates, total phosphorus, toxic pressure (chronic msPAF) and chlorophyll-a. Each model is described by its family distribution, link function, the percentage of deviance explained, and the restricted maximum likelihood (REML) estimate. For each parameter, the table presents the calculated parametric coefficients, including the intercept and its statistical significance, along with smooth terms for trends, seasonal effects and their interactions. The significance of each term is indicated by its *p*-values, with symbols denoting levels of significance: '***' for highly significant ($p < 0.001$), '*' for significant, and no symbol for non-significant results.

	Family	Link	Explained deviance	REML	Parametric coefficients	Estimate	Std. Error	t	p-value	Smooth terms	edf	Ref.df	F	p-value
Residence time	Gamma	Log	66.31	148	Intercept	3.60	0.36	5.18	< 0.001***	Season	6.44	8.00	4.33	< 0.001***
					Inflow	0.00	0.24	−1.76	0.087					
Temperature	Gaussian	Identity	97.64	25,998	Intercept	18.99	0.10	2902	< 0.001***	Trend	8.79	8.99	446	< 0.001***
										Season	7.99	8.00	100,182	< 0.001***
										Trend X Season	15.1	15.9	67.7	< 0.001***
Conductivity	Gamma	Log	74.54	3903	Intercept	7.58	0.17	712	< 0.001***	Trend	46.7	55.3	9.56	< 0.001***
										Season	0.52	8.00	0.08	0.040*
										Trend X Season	26.5	31.8	6.28	< 0.001***
Nitrate	Tweedie	Log	45.89	747	Intercept	1.54	0.25	48.86	< 0.001***	Trend	9.58	11.5	7.65	< 0.001***
										Season	4.77	8.00	14.4	< 0.001***
										Trend X Season	5.67	7.59	3.29	0.002*
TP	Gamma	Log	43.27	−199	Intercept	−1.57	0.43	−39.62	< 0.001***	Trend	11.0	13.1	12.0	< 0.001***
										Season	1.24	18.0	0.11	0.175
										Trend X Season	7.81	10.1	2.39	0.010*
Chronic msPAF	Gaussian	Log	52.40	−90.58	Intercept	−3.43	0.33	−10.53	< 0.001***	Trend	1.00	1.00	9.15	0.003*
										Season	13.2	18.0	3.18	< 0.001***
										Trend X Season	4.41	5.57	5.40	< 0.001***
Chlorophyll-A	Gaussian	Log	55.00	3621	(Intercept)	4.82	0.43	91.25	< 0.001***	Trend	16.0	19.6	11.7	< 0.001***
										Season	7.16	8.00	32.0	< 0.001***
										Trend X Season	11.8	13.6	4.39	< 0.001***

shows the occurrence of heatwaves in the years 1971, 1975, 1982, 2003, 2003, 2010, 2013, and in each year between 2015 and 2022 (Fig. S2). In recent years, heatwaves have become more common and longer lasting, and their severity (i.e., increase in mean temperature deviation) has also been intensified, leading to regular episodes of water temperatures above 30 °C (Table S1).

In the case of the conductivity model, the Gamma model with log as the link function provided the best fit, as illustrated in Table S2. All temporal components were found to have a significant effect (Table 1). The yearly average conductivity values have decreased slightly during the study period (from 1837 ± 589 μS/cm in 1972 to 1578 ± 239 μS/cm in 2022). The maximum conductivity values were reached in 1995 (4648 μS/cm), coinciding with one of the lowest inflow periods into the lake, and the minimum in 2020 (827 μS/cm) after a heavy rain period in November. The seasonal pattern shows conductivity increases during the winter months and decreases during spring and summer. The long-term trend is slightly negative, although the tensor product heatmap shows that in recent years there are seasonal increases in conductivity, which are concentrated in the summer period (Fig. 3). The model explains 75 % of the total deviance.

In the context of modelling the nitrate concentration time series, the Twedie family models were selected given that the response variable is strictly non-negative and includes zero-inflated observations (Table S2). In the nitrate model, both the trend and seasonality, along with their interaction through the tensor product, had significant effects. An upward trend of nitrate concentrations was noticeable up to 1995, with mean yearly concentrations of 7 mg/L and peak concentrations of 25 mg/L. Since then, the nitrate concentrations experienced a decrease until 2010, with annual average levels reaching up to 10 mg/L, albeit with lower peak concentrations. The trend was maintained until 2020, when it experienced a mild reduction, with mean yearly concentrations around 4 mg/L in 2022 (Fig. 3). The tensor product shows the greater seasonal contrast in nitrate concentrations prior to 1990, while in recent years nitrate concentrations have been more constant throughout the year. The model was able to explain 46 % of the total deviance (Table 1).

In the case of the TP model, the Gamma model with log as the link function was identified as the optimal fit based on the distribution characteristics (Table S2). Regarding temporal patterns, it was observed that the maximum concentrations of TP occurred around the 1990s (Fig. 3), with a maximum yearly mean concentration reaching 1.1 mg/L in 1987. Then, there was a yearly mean decline in concentrations until 2003 (0.09 ± 0.05 mg/L), after which it began to gradually increase until 2012 (0.38 ± 0.26 mg/L). Following this, there was another decline until 2017, when the minimum yearly mean was reached (0.07 ± 0.05 mg/L). After 2019, the trend appears to reverse, with a slight increase in TP concentrations observed in 2022 (0.20 ± 0.10 mg/L). TP concentrations were found to increase during the periods of maximal primary production, in May and June, although the seasonal component is not significant. As in the case of nitrate, the tensor product reveals a large seasonal contrast between the 1970s and 1990s, while in recent years it has remained more constant. The model explained 43 % of total deviance (Table 1).

The toxic pressure data series contained 170 observations, out of which 68 (40 %) exceeded the threshold established for the determination of unacceptable toxic effects (i.e., 5 % of species potentially affected; Posthuma et al., 2019). Aluminium and zinc were identified as the most notable and recurrent contributors to aquatic toxicity (Fig. S4A). Regarding the chronic toxic pressure model (chronic msPAF), Table S2 indicated that the best fit was provided by the Gaussian model with log as the link function. The model has an increasing and significant long-term trend (Table 1). The seasonal pattern is significant and marked by some toxic pressure peaks (Fig. 3). When categorized into organic and inorganic compounds, we found that inorganic pollutants remain somewhat constant, while pesticides, exhibit seasonal peaks

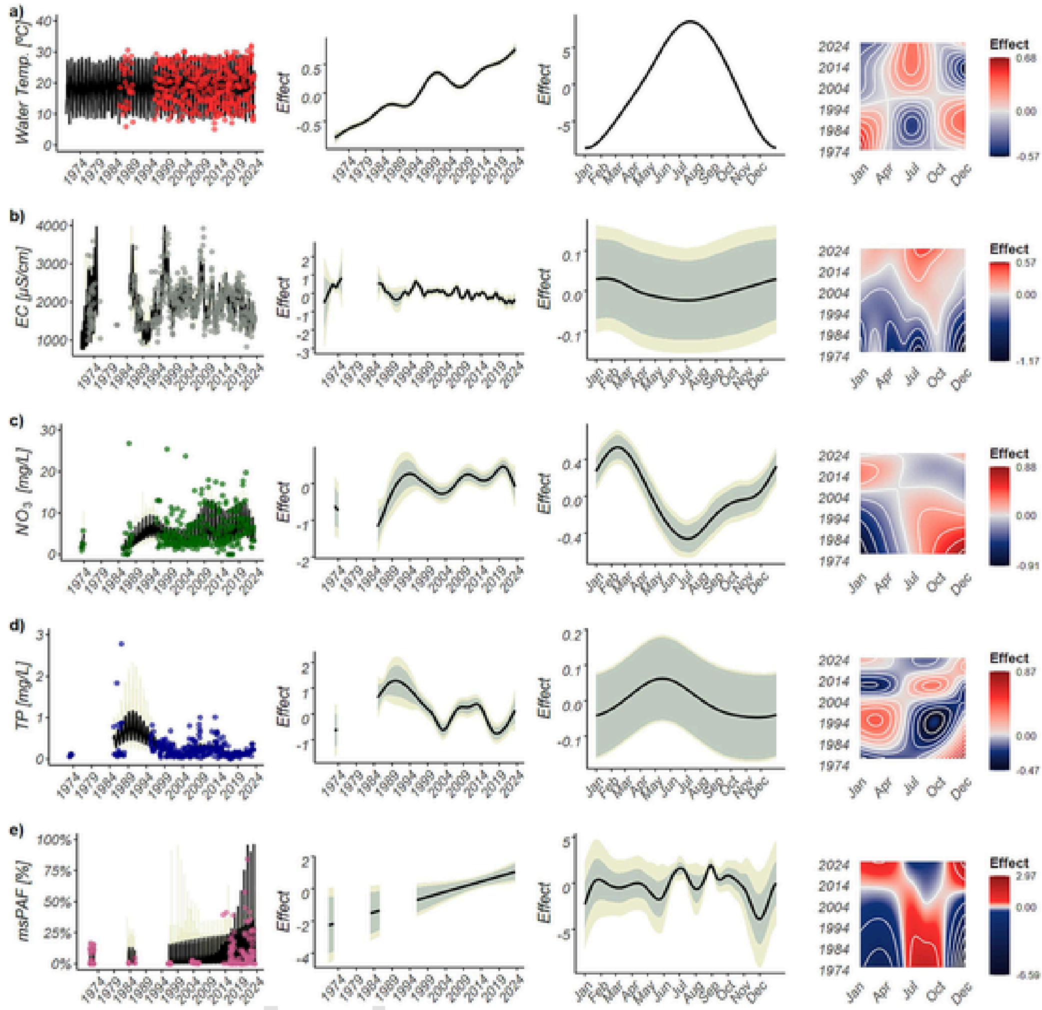

Fig. 3. Temporal patterns of water temperature, electrical conductivity, nitrate concentration, total phosphorus (TP), and chronic msPAF in the Albufera lake. From left to right the graphs show the measured (dots) and modelled (line) data trend, the partial effects associated with the long-term trend, the seasonal component, and the heatmap representing the tensor product of the seasonal (x-axis) and the trend (y-axis) components as result of the GAM analysis. In the heatmap, darker blue colour indicates negative effect of the tensor product on the response variable, while red indicates a positive effect. In the graphs showing the partial effects of the long-term trend and the seasonal component, pointwise confidence intervals are depicted in grey, while the parsimonious confidence intervals are illustrated in light yellow.

during the rice growing season (Fig. S4B). The chronic toxic pressure model explains 52 % of the deviance within the dataset (Table 1).

The chlorophyll-a temporal model revealed significant effects of both the trend and seasonal components, along with their interaction (Table 1). Chlorophyll-a was found to increase from 13 ± 6.3 µg/L in the 1970s until 1983, when the maximum chlorophyll-a values were reached: 456 ± 163 µg/L (Fig. 4). Then, it remained rather stable between the 1990s and 2000s, with mean yearly concentrations around 150 µg/L. The lowest chlorophyll-a values occurred in 2017, with a yearly mean of 68 ± 43 µg/L. The study of the seasonal pattern evidences the existence of two annual chlorophyll-a peaks, one in spring (end of May), when the rice growing season starts, and another one in October, after the emptying of the rice fields. The tensor product reveals recent changes in chlorophyll-a seasonality, with the first peak occurring earlier in spring as compared to the previous years (Fig. 4). The model explained 55 % of total deviance (Table 1).

Model diagnostics and autocorrelation plots can be found in Fig. S1 and S2 for the stressors, and in Figs. S6 and S7 for chlorophyll-a. In general, no significant autocorrelations were detected, with only a few moderate and isolated instances observed, as demonstrated by the ACF and pACF plots. Therefore, we did not incorporate explicit autocorrelation structures in the models.

3.2. Multiple stressor effects on chlorophyll-a

The GAM model used to assess the influence of the selected stressors on chlorophyll-a concentration explained 76 % of the total deviance (Table 2). Seasonality, temperature, water residence time, and TP had significant effects (Fig. 5), alongside the tensor product interactions between temperature and conductivity, conductivity and nitrates, conductivity and residence time, and nitrates and TP (Fig. 6). Although conductivity and toxic pressure (msPAF) alone were not individually significant, their interactions with other variables, such as conductivity with msPAF, showed notable effects in the model. The model was fitted using a Gaussian family with a logarithmic link function and achieved a Restricted Maximum Likelihood (REML) value of 2678, supporting the robustness of the selected model. The remaining tested configurations, along with model quality metrics, can be found in Table S3.

The integration of tensor products in the model allows for adjustments to the relationships described above for specific situations, providing more flexibility in capturing complex interactions. For instance,

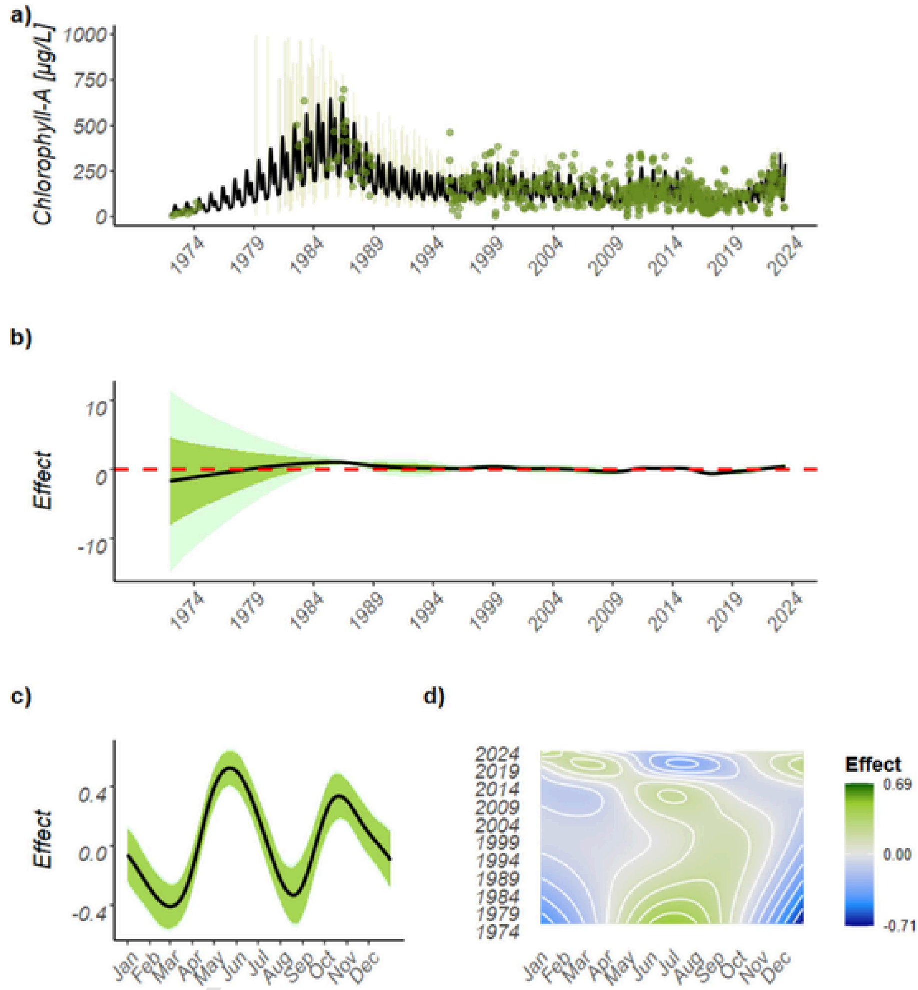

Fig. 4. Temporal components of the chlorophyll-a GAM: a) represents the results of the modelled (line) and the observed (dots) chlorophyll-a concentration; b) the partial effects associated with the long-term trend; c) shows the seasonal component; and d) shows the heatmap representing the tensor product of the seasonal (x-axis) and the trend (y-axis) components. In panels b), and c), the pointwise confidence intervals are depicted in dark green, whereas the parsimonious intervals are illustrated in light green.

at higher temperatures, when conductivity is low, the interaction leads to an increase in chlorophyll-a, while at conductivities above 2000 μS/cm, the effect becomes negative, reducing chlorophyll-a levels. At lower temperatures and low conductivity, the interaction also has a negative effect on chlorophyll-a. The interaction shows considerable diversity, with different patterns emerging across the range of temperatures and conductivities. At low temperatures and low conductivity values, negative synergies are observed, while at moderate temperatures (around 20 °C) and medium conductivity levels, negative antagonisms dominate. Positive synergies emerge at temperatures approaching 30 °C with low conductivity.

The interaction between conductivity and nitrate concentrations results in maximum values of chlorophyll-a when nitrate levels exceed 20 mg/L and conductivity exceeds 2500 μS/cm. Negative synergic effects appear when the nitrate concentration is low (< 3 mg/L) and water conductivity is lower than 2000 μS/cm, while positive synergies arise when conductivity exceeds this threshold. Antagonisms are distributed around conductivities of approximately 2000 μS/cm, showing predominantly positive antagonism when nitrate concentrations are below 5 mg/L and negative antagonism at higher nitrate concentrations.

The interaction between conductivity and toxic pressure, represented by the chronic msPAF, remains largely neutral across most combinations, with values near zero in most cases. However, when conductivity is low, and the toxic pressure is high, positive effects on chlorophyll-a emerge. Additionally, at high toxic pressure levels (above 35 % of species affected), negative effects on chlorophyll-a are observed when conductivity exceeds 3000 μS/cm. Regarding stressor interactions, three distinct patterns can be observed. Two regions of synergies appear below 2000 μS/cm: negative synergies occur when the toxic pressure is low, and positive synergies arise when toxic pressure ranges between 5 % and 25 % of species affected. Additionally, negative antagonisms are found when the toxic pressure is between 0 % and 10 % of species affected and conductivity ranges from 2000 to 3000 μS/cm.

The interaction between conductivity and residence time reveals two main scenarios where negative effects dominate. The first occurs when conductivity is low (around 1000 μS/cm) and residence time is moderate (between 20 and 60 days), while the second appears when conductivity is high (above 3000 μS/cm) at elevated residence times (> 50 days). However, at these higher residence times, the effects on chlorophyll-a become positive when conductivity is low. Regarding stressor interactions, negative synergistic effects were observed at high conductivity values and high residence times, as well as at moderate residence times (between 20 and 40 days) and low conductivity. Negative antagonisms occur at conductivities around 2000 μS/cm, especially when the residence time is low (below 20 days).

Table 2
Summary of the GAM model developed to predict the effect of different stressors on chlorophyll-a concentration. The model employs a Gaussian family with a logarithmic link function and explains 75.77 % of the deviance, with a Restricted Maximum Likelihood (REML) value of 2678. The parametric coefficient for the intercept is estimated at 4.69, with a standard error of 0.03, resulting in a highly significant t-value of 154 and a p-value of < 0.01.The table shows the smooth terms with their respective standard errors, F-values, and p-values to assess statistical significance, with symbols denoting levels of significance: '***' for highly significant ($p < 0.001$), '*' for significant, and no symbol for non-significant results.

Smooth terms	edf	Ref. df	F	p-value	
Season	12.17	18.0	5.47	< 0.001	***
Residence time	6.75	7.71	2.90	0.005	*
Temperature	1.00	1.00	8.16	< 0.001	***
Conductivity	1.00	1.00	3.65	0.056	
Nitrate	7.11	8.12	3.53	0.001	*
TP	6.26	7.12	11.35	< 0.001	***
Chronic msPAF	1.02	1.04	0.40	0.521	
Temperature × Conductivity	9.11	10.84	4.63	< 0.001	***
Conductivity × Nitrate	6.14	7.37	10.6	< 0.001	***
Conductivity × msPAF	8.74	10.18	3.21	< 0.001	***
Conductivity × RT	6.08	7.33	2.99	0.004	*
Nitrate × TP	7.84	8.96	5.44	< 0.001	***
TP × Residence time	3.12	3.83	2.19	0.142	

The interaction between nitrate concentrations and TP tends to a neutral effect in most combinations, except when nitrate levels exceed 15 mg/L. In these cases, the effects on chlorophyll-a become positive when phosphorus levels are low to moderate (below 0.5 mg/L). However, as TP concentrations are between 0.5 and 3 mg/L, the interaction results in negative effects on chlorophyll-a. Once TP exceeds 3 mg/L, the effects return to be positive. Negative antagonisms dominate at low TP and medium nitrate levels. As nitrate concentrations decrease, and TP concentrations are low (< 0.5 mg/L), negative synergies appear.

The interaction between TP and residence time, although was not statistically significant, was retained in the model because removing it would lead to a significant increase in the AIC. The pattern reveals positive effects on chlorophyll-a at high TP concentrations and high residence times. Positive antagonistic effects were observed when TP levels are < 0.5 mg/L across nearly the entire range of residence times.

3.3. *Water quality management*

A total of 940,900 variable combinations (out of the 3,650,000 evaluated) resulted in chlorophyll-a concentrations below 30 μg/L, with seasonal fluctuations observed in the frequency of these combinations. Winter months exhibit a higher number of potential combinations, reaching up to 7348 combinations on certain days, whereas in the spring-summer period, the count significantly drops, with some days showing only one combination of variables predicting chlorophyll-a levels below the water quality targets. Clustering of the observations using k-means revealed the existence of two major pathways to achieve the management targets, which were termed as ´the brackish water state´ and ´the freshwater state´, due to their differences in conductivity. The brackish water state has a mean annual conductivity of 3019 μS/cm, a mean residence time of 12.3 d, a mean TP concentration of 0.02 mg/L, and a mean nitrate concentration of 7.93 mg/L. The freshwater state, on the other hand, showed a mean conductivity of 1821 μS/cm, a mean residence time of 8.14 d, a mean TP concentration of 0.02 mg/L, and a mean nitrate concentration of 8.04 mg/L. The monthly averages for each of the simulated stressors needed to achieve the water quality targets set by the WFD in each of the two states are shown in Fig. 7.

4. Discussion

4.1. *Multiple stressor trends*

Analysing the temporal dynamics of various stressors allowed for a detailed understanding of the changes in the ecological status of the Albufera Lake over the last fifty years. In terms of hydrology, our study shows a clear decrease in the water inflow with a consequent increase in the lake's residence time. This can be tied back to the improved efficiency of irrigation practices in the surrounding agricultural areas, which prevents water seepage into the lake, and the increased water recirculation within the lake system for rice irrigation (Martín et al., 2020). We also observe the influence of the rice growing cycle on the seasonal hydrological patterns of the lake, with residence times being notably reduced during the two principal draining phases of the rice paddies: following the winter flooding and immediately after harvesting.

A particularly concerning finding is the increasing trend in water temperatures due to climate change. Rising temperatures associated with global warming have the potential to profoundly impact shallow lakes. High water temperatures can lead to reduced dissolved oxygen levels, altered nutrient cycling and decomposition rates, and increased growth of harmful algal blooms (Paerl and Huisman, 2008; Paerl et al., 2011; Morant et al., 2020; Salimi et al., 2021). Additionally, rising temperatures may disrupt the timing of critical life cycle events of birds, such as breeding and migration, leading to mismatches with food availability and potentially reducing overall population sizes (Bates et al., 2008; Chandler et al., 2016). The increasing frequency and severity of heat waves, both in the Albufera Lake and globally due to climate change, have been linked to direct impacts on the metabolism, physiology, and behaviour of organisms, as well as indirect effects on individual growth and reproductive success of aquatic organisms, leading to shifts in community dynamics (Polazzo et al., 2022b). Heat waves can also play an important role in maintaining aquatic ecosystems in a turbid phase by influencing macrophyte communities and their interactions (Li et al., 2017). Of particular importance is the temporal change in phytoplankton dominance that has been observed in the Albufera Lake during 2023, presumably due to a prolonged episode of elevated water temperatures. Further, it has also been shown that increasing water temperatures may affect the fate and effects of toxic compounds such as pesticides in the Albufera Natural Park, reducing the abundance of zooplankton grazers and fostering the increase of phytoplankton biomass (Vilas-Boas et al., 2021; Martínez-Megías et al., 2023; Hermann et al., 2024).

The salinization of freshwater coastal wetlands has undergone a significant surge worldwide due to human-induced factors, including the use of road de-icing salts, agricultural practices, resource mining, and the effects of climate change (Cañedo-Argüelles et al., 2016; Kaushal et al., 2018). Empirical evidence supports the notion that salinization exerts profound effects on freshwater ecosystems, leading to decreased growth and abundance of vulnerable species, reduced biodiversity, shifts in community composition, and alterations in ecosystem functioning (Hintz and Relyea, 2019; Cunillera-Montcusí et al., 2022). The case of the Albufera Lake is special, as until the 18 th century it was a hypersaline wetland, until its connection with the sea was closed for rice cultivation (Soria et al., 2021b). Nowadays, it is considered an oligohaline wetland, with an average conductivity of around 2103 μS/cm. Despite this, the wetland still has a marked saline influence, especially in the deeper soil horizons and due to sub-surface flow from the Mediterranean Sea (Moreno-Ramón et al., 2015). Previous studies conducted in the Albufera Lake concluded that floods and irrigation practices influence conductivity levels, with increased water supply decreasing conductivity, and reduced inflow leading to a moderate salinity intrusion (Soria and Vicente, 2002; Soria et al., 2021b). Here, we found a slightly negative long-term trend in conductivity, which con-

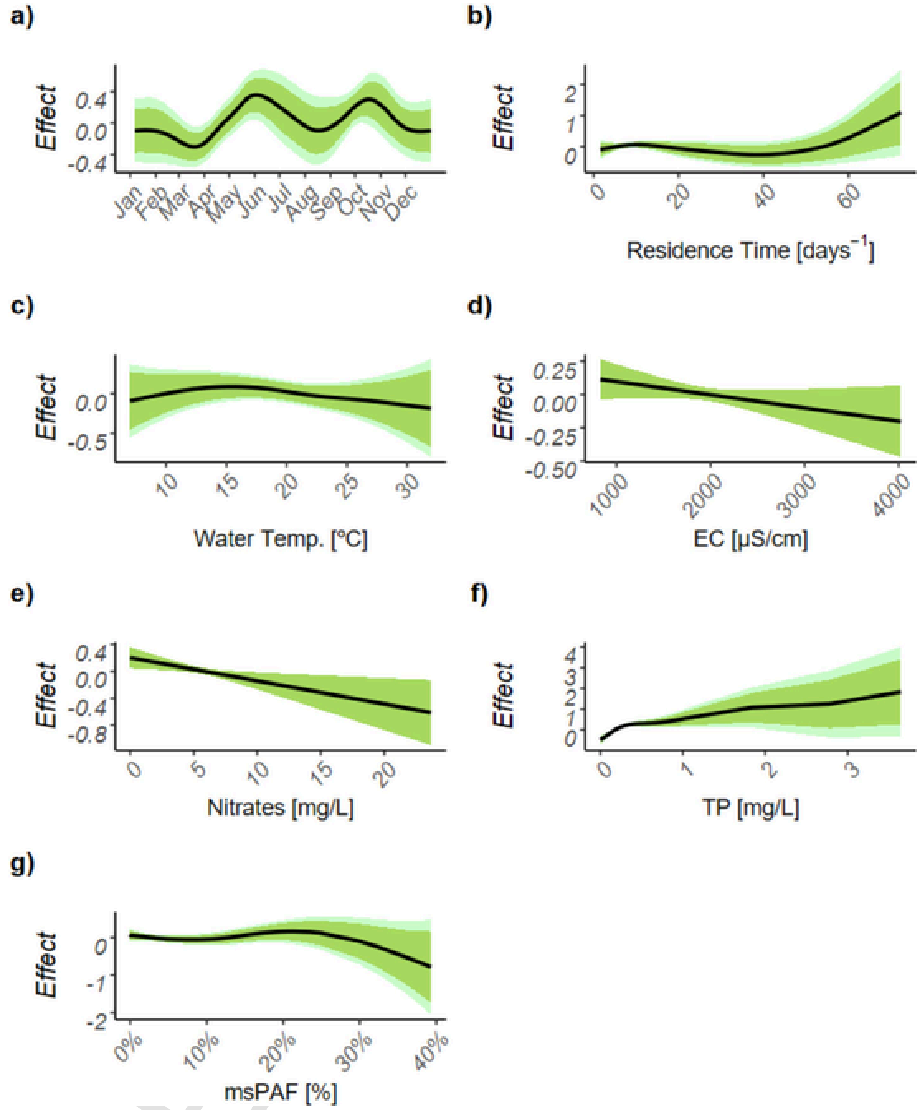

Fig. 5. Partial effects of the individual smooths in the chlorophyll-a predictive GAM. a) represents the seasonal effect; b) the partial effect of temperature; c) the partial effect of residence time; d) the partial effect of conductivity; e) the partial effect of chronic toxic pressure (msPAF); f) the partial effect of nitrate; and g) the partial effect of total phosphorus (TP). Effects on chlorophyll-a are positive when each of the smooths takes positive values, and negative when they are negative. Pointwise confidence intervals are depicted in dark green, whereas the parsimonious intervals are illustrated in light green.

trasts with the results shown by Soria et al. (2021b). Nevertheless, our results do show a seasonal increase in recent summers. This circumstance hinders the long-term trend's ability to incorporate this deviance and may explain the different results as compared to those shown by Soria et al. (2021b). The summer increases in conductivity could be attributed to reduced water inflow during this season and the impacts of climate change, as evidenced by the water temperature's tensor product and trend showing substantial increases in water temperature, especially during the summer months. The seasonal pattern of conductivity also evidences the influence of rice flooding periods on the functioning of the lake, with the winter months, where the rice fields are flooded and residence time increases, showing a positive effect on conductivity. In contrast, during the summer, the lake functions more like an estuary, leading to a negative seasonal effect, despite the already mentioned recent summer seasonal increase.

A substantial body of scientific literature has explored the causes and effects of nutrient loads into the Albufera lake, from the 1970s to the present (Blanco and Hernández Giménez, 1974, Soria et al., 1987, Romo and Miracle, 1994, Romo et al., 2005, Romo et al., 2008, Onandia et al., 2015, Martín et al., 2020). Throughout this temporal span, several measures have been implemented, encompassing initiatives such as the establishment and improvement of Wastewater Treatment Plants (WWTPs) as well as the creation of constructed wetlands, engineered to serve as green filters, which have proven successful in nutrient and pollutant removal both in the Albufera and worldwide (Martín et al., 2020; Pipil et al., 2021; Martínez-Megías et al., 2024). Nonetheless, the problem persists, likely due to the lake feedback mechanisms, the historical sequestration of nutrients in the sediment, and the enduring influence of diffuse pollution from urban and agricultural sources (Martín et al., 2020). Both nitrate and TP modelling results illustrate that the maximum nutrient input to the lake occurred around the 1990s. Since then, TP has declined considerably, while nitrates have remained relatively stable, probably due to the diffuse nature of nitrogen pollution. The seasonal patterns of both nutrients are opposite. Due to the rapid uptake of dissolved nitrates by phytoplankton, seasonal minimum levels are observed during periods of high primary production. Conversely, maximum nitrate levels are recorded during the winter season when less favourable light and temperature conditions

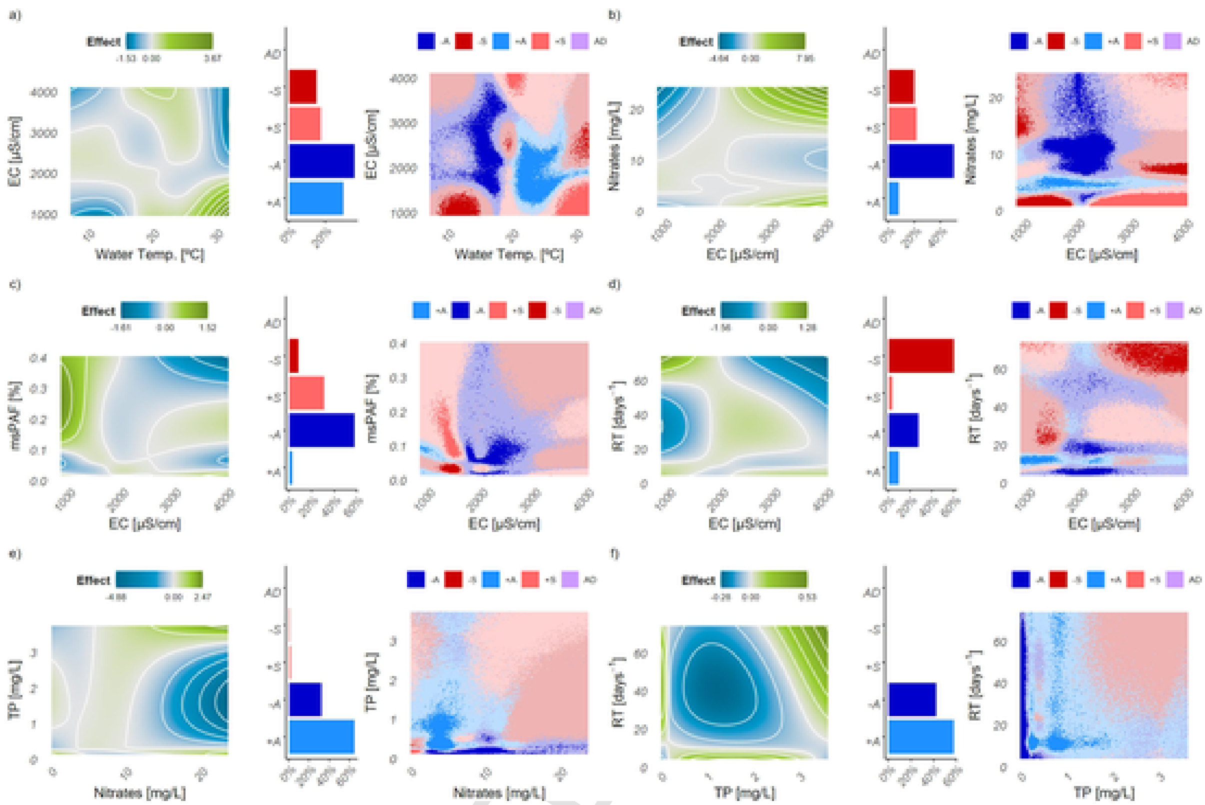

Fig. 6. Stressor interactions identified by the chlorophyll-a GAM: a) temperature and conductivity; b) conductivity and nitrates; c) conductivity and residence time; d) nitrates and total phosphorus (TP); e) conductivity and msPAF; and f) total phosphorus (TP) and residence time. From left to right, columns represent a heatmap of the tensor products of the chlorophyll-a predictive model, the relative abundance of the interaction types established by Piggott et al. (2015) keeping only those cases that were confidently classified (with >90 % consistency), and a heatmap indicating the specific combinations of variable values at which each interaction type occurs. Letters indicate additive (AD), positive synergistic (+S), negative synergistic (—S), positive antagonistic (+A), and negative antagonistic (–A) effects. Transparency in the interaction type heatmap was increased for observations that were less confidently classified (i.e., after sampling the posterior distributions of the smooths, changed the interaction category in >10 % of cases).

prevail. It is worth noting that this phenomenon can obscure the fact that the spring and summer seasons typically experience the highest gross inputs (Onandia et al., 2015). It is very likely that increases observed by Onandia et al. (2015) in nitrogen and phosphorus levels are a consequence of fertiliser application during rice cultivation, since the highest increases reported by these authors were observed in May and July, which align with the fertilisation periods. Our study suggests that there is a shift of the seasonal minimum values in recent years towards September; probably due to the effects of raising temperatures and primary productivity during autumn. TP, on the other hand, reaches its seasonal maximum in May, where the optimum temperatures for primary production coincide with the fertilisation of the paddy fields.

The analysis of the long-term trends of toxic pressure over the Albufera Lake showed that zinc and aluminium are the most prevalent and hazardous pollutants for freshwater organisms. Zinc is a limiting nutrient for rice and is commonly supplemented during cultivation, while aluminium arrival to aquatic ecosystem is mostly related to industrial processes (Lin et al., 2019; Zulfiqar et al., 2021). In fact, aluminium salts are frequently used in water depuration (Lin et al., 2019). The two highest contamination peaks for aluminium occur after heavy rainfall events (above 100 mm), suggesting that aluminium entry might be related to sudden (untreated) wastewater discharges or due to runoff from nearby industrial areas. The primary finding derived from the GAM modelling of the chronic msPAF are the changes in toxic pressure over time, with the long-term trend showing a large effect on model predictions. Chemical monitoring is expensive, and risk quantification is highly dependent on the substances measured. Therefore, the evolution of the toxic pressure indicator is related to the chemical monitoring efforts and the selection of substances to be analysed. Between the 1970s and the 1990s, only a limited number of substances were quantified, and even though some of them were very toxic and bioaccumulative (e.g. organochlorine pesticides), the calculated toxic pressure obtained by those is lower than in more recent years. This does not mean that toxicological hazards did not exist in that period, but chemical monitoring was limited in terms of substance number and temporal resolution. After the establishment of the Water Framework Directive, monitoring efforts by local administrations and the Júcar River Basin Authority agency have facilitated more consistent monitoring of these chemicals, with some samples resulting in chronic toxicity for up to 80 % of species. Consequently, a discernible long-term upward trend is found. The results from the tensor product analysis further illustrate this pattern, highlighting positive effects during summer in the 1970s, a period when sampling efforts were concentrated and high toxicity peaks were observed due to specific pesticide applications, such as fenthion used to control rice borers. In contrast, current sampling efforts are more evenly distributed throughout the year. This leads to negative effects in the tensor product during summer, while the effects in the remaining seasons are positive. Seasonal analysis of pesticide toxicity reveals a consistent peak during the rice-growing season across different time periods. Summer toxic pressure was influenced by organic pesticides such as azoxystrobin or chlorpyrifos, which have been shown to affect micro- and macro-crustacean populations, both for species representative of the ANP (Vilas-Boas et al., 2021; Amador et al., 2024) and

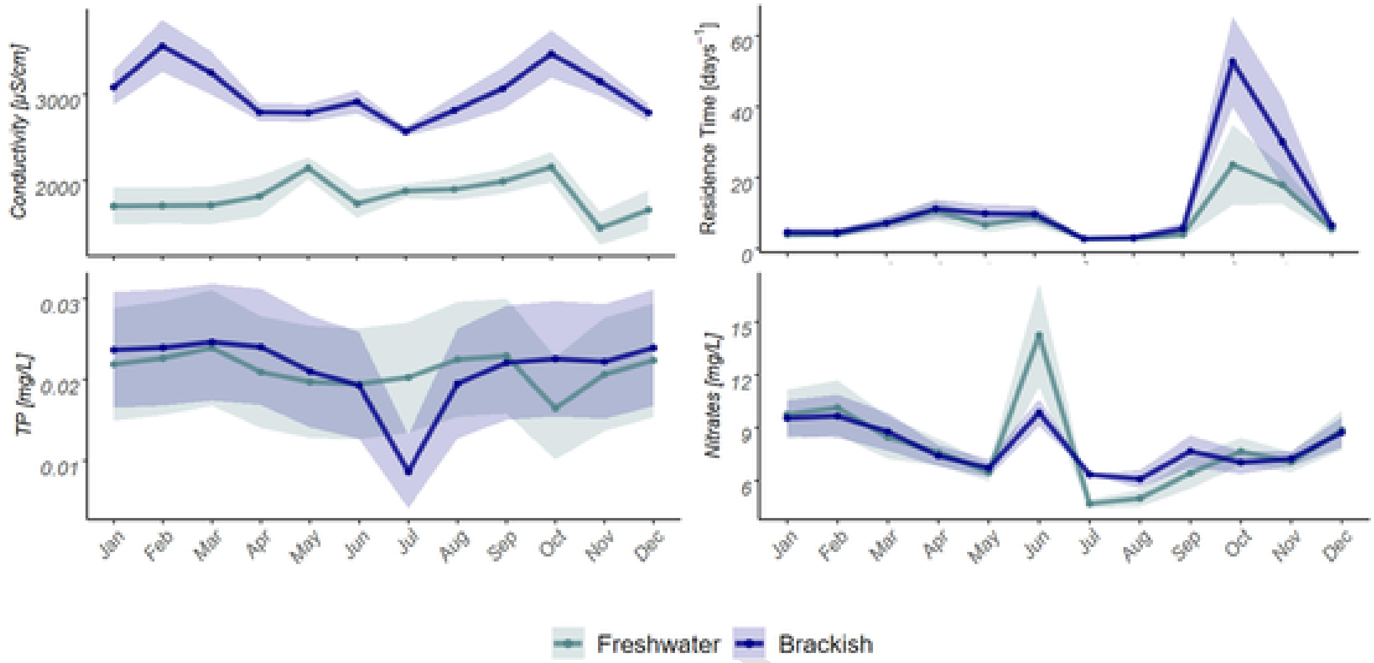

Fig. 7. Monthly mean and standard deviation of the stressor values needed to reach a water quality target of 30 µg/L of chlorophyll-a for two the distinct clusters of observations identified using the k-means analysis, namely the ´brackish´ and the ´freshwater´ state.

for mediterranean surface water ecosystems in general (López-Mancisidor et al., 2008).

Our modelling results show that the yearly mean chlorophyll-a concentration is a key indicator of the eutrophication status of the system, increasing rapidly since the 1970s and peaking in the 1980s due to factors like rapid population growth, industrialization, and untreated wastewater discharges. The construction of WWTPs led to a stabilization of chlorophyll-a levels around the mid-1990s, allowing an average concentration of approximately 150 µg/L during the next decades. Our analysis also shows that typical chlorophyll-a spring peaks are taking place earlier in the season, and possibly associated to the increasing water temperatures due to climate change.

4.2. *Multiple stressor effects on chlorophyll-a*

Key drivers of eutrophication in Albufera Lake, based on the results of the GAM model, include water temperature, residence time, nitrates, and seasonality, all of which significantly impact algal productivity. Notably, while conductivity alone and toxic pressure (msPAF) were not individually significant, their interaction with other variables, still played a significant role in the model.

Warmer temperatures promote accelerated algal growth, due to metabolic rates increase and reproduction in the presence of nutrients (Schaum et al., 2017). Furthermore, warmer temperatures can also influence water stratification patterns, creating favourable conditions for phytoplankton dominance in the top layer (Winder and Sommer, 2012). Similarly, longer water residence periods facilitate nutrient assimilation, and prevent phytoplankton being exported out of the system (Stumpner et al., 2020). In the Albufera Lake, it has been shown that longer residence times are particularly beneficial for some species of slow-growing cyanobacteria, such as *Microcystis* sp., or for those favoured by water stability, such as *Aphanocapsa* sp. (Romo et al., 2013). Our study also shows that conductivity is a crucial factor influencing the chlorophyll-a concentration in the Albufera Lake, with extreme conductivity values reducing chlorophyll-a levels. Also, high toxic stress by chemical mixtures (msPAF values above 30 %) decreased chlorophyll-a concentration in the Albufera Lake throughout the year, possibly due to transient toxic effects on phytoplankton.

Our results show that the occurrence of additive effects is low, which supports the theory that interactions between multiple stressors commonly result in non-additive effects and vary temporally (Jackson et al., 2016, 2021). One of the most prominent findings is the high prevalence of antagonistic interactions, which typically occur when there is a clear dominance of one variable over the other (Jackson et al., 2016). This suggests that some stressor interactions may play a buffering role in the development of phytoplankton biomass, as documented in previous studies (Polst et al., 2022). Such effects may stem from ecosystem's inherent resilience, allowing it to better withstand fluctuations and disturbances caused by environmental stressors. Moreover, in a management context, the rarity of additive interactions highlights the fine line between synergies and antagonisms. In fact, the danger of positive synergies lies in that narrow boundary where small changes can result in disproportionately large environmental impacts. A clear example of this dynamic is the interaction between high temperature peaks and low conductivity, which results in a disproportionate increase of chlorophyll-a, or the influence of high toxic pressure when conductivity levels are low. On the other hand, negative synergies allow for more efficient management strategies by reducing the combined impact of stressors, thereby minimizing efforts needed to achieve environmental objectives. This phenomenon is illustrated in the interaction between conductivity and residence time, where negative synergies occur at high levels of both. In such cases, the rise in salinity intensifies the negative impact on chlorophyll-a, despite the normally positive effects caused by low water recirculation.

4.3. *Implications for ecosystem management and way forward*

Our study points at two potential strategies to reduce chlorophyll-a concentrations in the lake, supporting a brackish or a freshwater state. The first would entail hydrological deregulation to facilitate seawater influx, leading to reduced residence times and higher conductivity levels. This would also probably mean giving up much of the rice cultivation that has shaped the wetland for centuries. However, these changes could have a beneficial impact on the fish stock, which has been severely affected by the current hydraulic management practices (Boelens and Claudín, 2015). The second alternative would imply increasing the external freshwater influx into the lake, thereby reducing salinity intrusion and accelerating the flushing rate of phytoplankton, nutrients and other contaminants. Grouping the observations likewise suggests the possibility of specific interventions in certain months, where chlorophyll-a levels can be brought under 30 μg/L with some adjustments to current water inflow rates.

The average residence time for the brackish scenario is 12.3 d, whereas it is 8.14 d for the freshwater scenario. A comparison of these residence times with those of 2022 reveals that the brackish state would need a total annual inflow of 218 hm^3 (11 % decrease) while the freshwater cluster a total of 417 hm^3 (70 % increase). Therefore, we show that to improve its ecological status, while maintaining the freshwater character of the wetland, the inflow of fresh water must be doubled. These figures are considerably higher than those presented by other authors (Soria and Vicente, 2002), and by the current hydrological plan (CHJ, 2016), which suggest a minimum yearly inflow of 260 and 210 hm^3, respectively. It should be noted, however, that both pathways are subjected to a TP reduction to of 0.05 mg/L, which would imply a reduction in TP by an order of magnitude when compared to 2022.

While these results highlight the importance of managing residence time and conductivity to reduce chlorophyll-a levels and improve its ecological status, it is important to acknowledge its limitations. Our analysis focuses on the analysis of observational data and does not account for the resistance of the system and the critical processes that contribute to maintaining its hypereutrophic status (Scheffer et al., 2009). These include, for example, contaminant and nutrient release from the sediment (Martín et al., 2020) and ecological factors such as the influence of fish on phytoplankton grazers, bird population dynamics, or the ecological influence of invasive species (Chaichana et al., 2010; Huser et al., 2022). Therefore, our findings should be viewed as a preliminary approach to identifying key variables and management actions that may contribute to improve the ecological status of the Albufera Lake in the short-term. A mechanistic understanding on how different water and contaminant management scenarios are affecting the resilience of the system in the long-term will be presented in a follow-up study that uses an ecosystem model to account for contaminant and nutrient management scenarios.

5. Conclusions

This study provides valuable insights into how multiple anthropogenic stressors are affecting the ecological status of a hypereutrophic lake. First, our analysis of the temporal dynamics of stressors over the past 50 years reveals that pressures on the Albufera Lake are highly dynamic. While some stressors, such as total phosphorus (TP), have been controlled, others, such as climate change, are on the rise, and issues like nitrate levels and chemical pollution remain partly unaddressed. Furthermore, our findings underscore the significance of rice farming and hydrological management on the ecological functioning of the lake. Second, the implementation of a GAM approach allowed the identification of the main stressors that affect the eutrophic status of the Albufera lake. The analysis of stressor interactions denoted a high prevalence of non-additive interactions and feedback mechanisms, which recognizes the importance of considering multiple stressor effects in environmental management and restoration. Third, our study indicates that to achieve the targets set by the WFD in the short-term, it is essential to increase the water inflow of the lake, especially if the goal is to maintain its freshwater characteristics. However, the increase in water inflow may not be effective in the long term if other measures such as reduction in nutrient and chemical loads are not effectively implemented.

CRediT authorship contribution statement

Pablo Amador: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Juan Soria:** Writing – review & editing, Methodology, Investigation. **Jesús Moratalla-López:** Writing – review & editing, Methodology, Investigation. **Andreu Rico:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

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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.

Acknowledgements

This study is part of the ERAHUMED project, funded by the Talented Researcher Support Programme - PlanGenT (CIDEGENT/2020/043) of the Generalitat Valenciana. We thank the support provided by the Albufera Biological Station. We also thank Gavin L. Simpson (Aarhus University) and two anonymous reviewers for their constructive comments on an earlier version of the manuscript.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.177247.

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