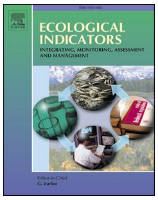
Ecological Indicators 184 (2026) 114685

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind



Setting safe ecological boundaries for nutrients and exploring climate impacts on biological resilience in lowland lakes and rivers in the Nordic and central European regions

Jan-Erik Thrane [a,*], Kirstine Thiemer [b], Areti Balkoni [a], Jens Fölster [c], Brian Kronvang [b], Juan Pablo Pacheco [b], Jukka Aroviita [d], Ainis Lagzdins [e], Ignacy Kardel [f], Geoff Phillips [g], Sandra Mingarelli [h], Gary Free [h], Anne Lyche Solheim [a]

[a] Norsk institutt for vannforskning (NIVA), Økernveien 94, Oslo 0579, Norway
[b] Aarhus Universitet (AU), Department of Ecoscience, Nordre Ringgade 1, Aarhus C 8000, Denmark
[c] Sveriges Lantbruksuniversitet (SLU), Almas Allé 8, Uppsala 750 07, Sweden
[d] Finnish Environment Institute (Syke), Marine and Freshwater Solutions, P.O. Box 413, 90014 Oulu, Finland
[e] Scientific Laboratory of Forest and Water Resources, Latvia University of Life Sciences and Technologies (LBTU), Akademijas iela 19, LV-3001 Jelgava, Latvia
[f] Department of Hydrology, Meteorology and Water Management, Warsaw University of Life Sciences, Ul. Nowoursynowska 166, Warsawa 02 787, Poland
[g] Biological and Environmental Sciences, University of Stirling, Stirling FK9 4LA, UK
[h] European Commission, Joint Research Centre (JRC), I-21027 Ispra, Italy

ARTICLE INFO

Keywords:
WFD
Ecological status
Nutrients
Climate
Modelling

ABSTRACT

Boundary concentrations for phosphorus and nitrogen set by EU countries and Norway are intended to support good ecological status in lakes and rivers. Yet these boundaries vary by more than an order of magnitude within comparable waterbody types, raising concerns that some limits may not ensure good status. This study estimates nutrient boundaries compatible with good ecological status for lake phytoplankton and river phytobenthos by using binomial logistic regression (BLR) and examines how climate variables affect their ecological status.

Using datasets on total phosphorus, total nitrogen and ecological quality ratios for lake phytoplankton and river phytobenthos from three Nordic and three Central European/Baltic countries, we estimated nutrient boundaries that are likely to support good ecological status for nutrient-sensitive biota in common lake and river types within each of these regions. The boundaries estimated with BLR correspond well to previous estimates based on other regression methods. Most of the currently used national boundaries are also in line with our estimates. However, some national boundaries exceed the upper 95% confidence limit of the estimated values – indicating that they may require further validation.

Climate effects on ecological status were variable and much weaker than the strong influence of nutrients. Nonetheless, ecological status for phytoplankton in lakes (expressed as normalized ecological quality ratio) showed a small but consistent negative relationship with summer air temperature for all the stratified lake types included. Consequently, river basin managers may need to adopt more stringent nutrient boundaries and/or implement additional measures to mitigate climate-driven risks to freshwater ecosystems.

1. Introduction

The objective set by the European Water Framework Directive (WFD) (EC, 2000) is that all water bodies in Europe should have been in at least good ecological status by 2015 unless exemptions are applied. In 2015, as well as in 2022, this target was only achieved for ~40% of all classified water bodies (EEA, 2024). One of the major reasons for this low level of achievement is nutrient pollution, which is still substantial

---

* Corresponding author.
E-mail addresses: jan-erik.thrane@niva.no (J.-E. Thrane), kirstine.thiemer@ecos.au.dk (K. Thiemer), areti.balkoni@niva.no (A. Balkoni), Jens.Folster@slu.se (J. Fölster), bkr@ecos.au.dk (B. Kronvang), jp@ecos.au.dk (J.P. Pacheco), Jukka.Aroviita@syke.fi (J. Aroviita), ainis.lagzdins@lbtu.lv (A. Lagzdins), ignacy_kardel@sggw.edu.pl (I. Kardel), phillips@stir.ac.uk (G. Phillips), sandra.mingarelli@ec.europa.eu (S. Mingarelli), gary.free@ec.europa.eu (G. Free), anne.lyche.solheim@niva.no (A.L. Solheim).

https://doi.org/10.1016/j.ecolind.2026.114685
Received 26 November 2025; Received in revised form 23 January 2026; Accepted 3 February 2026

in many countries, especially in agricultural areas due to diffuse nutrient runoff from overfertilized soils (Carpenter, 2005) and conventional tillage practices (Bechmann and Bøe, 2021; Liu et al., 2024). Climate change with more heavy rain events is likely to aggravate the situation due to the expected increase in nutrient runoff (IPCC, 2022). Urban wastewater also contributes to nutrient pollution, although less than previously (EEA, 2024). However, untreated sewage still pollutes Europe's surface waters due to leaks from aging sewers and rain-induced overflows (EEA, 2019), hindering further reductions in river biological oxygen demand (BOD) and ammonium during the last decade.[1]

The WFD nutrient target concentrations are identified through the boundaries between good (G) and moderate (M) status for total phosphorus (TP) and total nitrogen (TN) (and/or other nutrient variables) and should be set to achieve at least good ecological status for nutrient sensitive biological quality elements (BQEs), such as phytoplankton in lakes and phytobenthos in rivers (WFD, Annex V; Poikane et al., 2015). The currently used nutrient GM boundaries reported by most European countries have been questioned in terms of their ability to support good status for the nutrient sensitive BQEs (Poikane et al., 2019; Kelly et al., 2022). Nutrient thresholds supporting good status for the BQEs have therefore been estimated by various linear regression approaches using relationships between nutrient concentrations and intercalibrated biological metrics converted to normalized ecological quality ratios (nEQR) (Poikane et al., 2021 for rivers and Poikane et al., 2022 for lakes). The intercalibrated biological metrics used by most countries are species composition of phytobenthos in rivers (Kelly et al., 2009) and a combination of chlorophyll concentration, species composition and biomass or percentage of cyanobacteria for phytoplankton in lakes (Lyche Solheim et al., 2014; Phillips et al., 2014). The nEQR-scale spans from 0 to 1 and represents a deviation from reference conditions (nEQR close to 1). Thus, regardless of differences in reference conditions between the national BQE-indices, the nEQR values are comparable across countries for water bodies within common intercalibration types (Moe et al., 2023) and are well suited for pan-European analysis of ecological conditions for different BQEs in rivers and lakes (EEA, 2024; Lyche Solheim et al., 2025). The boundary between good and moderate ecological status has an nEQR value of 0.60. For phytoplankton in lakes, a decrease in nEQR means that the biomass increases and/or that the species composition changes towards species favored by high nutrient concentrations, including many cyanobacteria (Järvinen et al., 2013; Carvalho et al., 2013; Phillips et al., 2013).

Relationships between nEQR and nutrient concentrations are inherently noisy and heteroscedastic due to the presence of multiple pressures and confounding factors, which may compromise the statistical estimation of nutrient boundaries by traditional methods like linear regression. Therefore, other statistical approaches have been explored, such as binary logistic regression (BLR), which has been found advantageous and more robust compared to other techniques (Phillips et al., 2024). An online toolkit has been developed for this method to help countries set or validate nutrient boundaries that will support good ecological status for the nutrient sensitive BQEs (Varbiro et al., 2018). The main advantage of the BLR-method is adequate handling of misclassification rates caused by multiple pressures and confounding factors, i.e. data showing nEQR in poor status for a BQE despite low nutrient concentration, as well as the opposite situation where the nEQR for a BQE is in good status despite high nutrient concentrations.

An increasingly important knowledge gap is whether climate change can affect the resilience of BQEs to nutrient pollution. Climate change leads to warming, changing drought patterns (Stagge et al., 2017; Spinoni et al., 2017) and more extreme rainfall events (e.g. Rajczak and Schär, 2017). These changes affect the runoff of nutrients and other pollutants, which in turn may impact the BQEs through eutrophication, causing enhanced risk of harmful algal blooms and fish kills (Jeppesen et al., 2021; Sterner et al., 2020; Free et al., 2024). Rising temperatures will also lead to lower oxygen concentrations, possibly reducing the resilience of benthic fauna and fish to organic pollution and cause a shift of cold-water species towards warm-water species (Basen et al., 2022). Prolonged thermal stratification in lakes may reduce hypolimnion oxygen concentration and thereby increase the risk of anoxic sediments triggering internal phosphorus loading and methane emissions (Shi et al., 2024).

When assessing climate effects in this study, we wanted to account for the effects of TP concentration and broad spatial patterns, in order to estimate the “direct” effect of climate variables on nEQR for water bodies with comparable nutrient levels and geographical location.

Based on the general challenges and existing knowlegde outlined above, this study aims to answer the following four research questions:

- What concentrations of TP and TN, as estimated by BLR, are likely to support good ecological status for nutrient-sensitive biota in different types of lowland lakes and rivers in Northern and Central Europe?
- Are the current national nutrient target concentrations in line with those estimates?
- How do the the BLR-estimated nutrient ranges compare with existing estimates given by other regression methods?
- What are the impacts of temperature and precipitation on the ecological status of phytoplankton in lakes and phytobenthos in rivers?
    - o how much of the total variation in nEQR can be assigned to climate variables relative to nutrients and geographical location?
    - o what is the strength and direction of any significant climate effects?

A final objective is to use the findings from the study to provide guidance to water managers on setting safe ecological boundaries for nutrients also taking climate impacts on nutrient-sensitive biota into account.

2. Materials and methods

2.1. Dataset and water body types

Monitoring data, mostly from the time period from 2009 to 2020 were compiled from lowland river- and lake water bodies (WBs) in the Nordic (Norway, Sweden, Finland) and Central-European, including Baltic (hereafter called “Central-Baltic”), regions (Denmark, Poland, Latvia). The data were collected from public databases established by national environmental authorities responsible for the WFD monitoring and implementation. The data included average concentrations of TP and TN, and nEQR values for nutrient sensitive BQEs, i.e. phytoplankton in lakes and phytobenthos in rivers. The national metrics underlying the nEQR values for phytoplankton in lakes are mostly based on various combinations of chlorophyll *a* concentration, phytoplankton biovolume, trophic indices for taxonomic composition, and biomass of cyanobacteria (Lyche Solheim et al., 2014; Phillips et al., 2014). For phytobenthos in rivers, the national metrics are generally based on species composition indices, including a mixture of trophic and saprobic indices (Poikane et al., 2016; Kelly et al., 2009). These BQEs were chosen since the primary producers are expected to respond more directly to nutrient pollution than e.g. fish or benthic invertebrates. A list of the national metrics is given in the Suppl. Mat., Section 1.

Annual mean values of TP, TN and nEQR were available from several countries, but some provided long-term averages, i.e. mean over several monitoring years. To harmonize the data before estimation of GM boundaries, all data were aggregated to mean values per WB (see Suppl. Mat., Section 2 for details on data aggregation).

WBs belonging to different national types were grouped into

---

[1] Oxygen consuming substances in European rivers | European Environment Agency's home page

common types (so called intercalibration (IC) types, EC, 2024) which have been used for intercalibration of national classification systems for good ecological status (full description of IC types can be found in Suppl. Mat., Section 3). The analysis focused on lowland water types (Table 1), which are where most agricultural and urban areas are located.

The number of WBs varied from ca. 60 to ca. 450 per IC type in the Nordic region and ca. 60 to 700 per IC type in the Central-Baltic region (Table 1; Fig. 1).

In addition to the IC types in Table 1, data were also compiled from Nordic deep siliceous lakes (L-N2b), Nordic siliceous clearwater rivers (R-N2), as well as two Central Baltic river types (R-C1 small, siliceous, sandy rivers and R-C6 small calcareous rivers with gravel substrate). However, the data from these types did not allow robust estimation of boundaries due to insufficient data (L-N2b, R-C6 and R-N2) or a too poor statistical relationship between nEQR and nutrient concentration (R-C1; see table S5).

Within each IC type, data from several countries within each region (Nordic and Central-Baltic) were pooled to ensure that the data spanned a substantial part of the nutrient gradient within which the BQEs are known to respond to nutrients, e.g. from ~5 to 100 μg TP/L (Phillips et al., 2008 and Phillips et al., 2013; Schneider and Lindstrøm, 2011; Kahlert et al., 2023; see example in Fig. 2). Covering the entire TP gradient is necessary for robust estimations of GM boundaries for TP.

2.2. Data analysis for estimating good/moderate boundaries for nutrients

The GM boundary values were estimated using binomial logistic regression (BLR), as described by Phillips et al. (2024) and implemented in a statistical toolkit to assist with the development of nutrient concentrations that would support good ecological status for the Water Framework Directive (Varbiro et al., 2018). In short, the method estimates the probability of achieving at least good status (i.e., nEQR $\geq$0.6) over the range of nutrient concentrations (log transformed TP and TN) in the dataset. The estimated GM boundary is taken as the nutrient concentration corresponding to a certain probability (p) of achieving good status, termed a cutoff p value. The value of p is decided on as part of the analysis, with the aim of balancing the rate of misclassifications (false positive and false negative predictions) as well as obtaining an overall good classification accuracy. A detailed description of the BLR method sensu Phillips et al. (2024), including the procedure for evaluating data quality, model fit and choosing the cutoff p value, is described in Suppl. Mat., Section 4.

BLR models were fitted separately for each IC type covered by the data (Table 1). Confidence intervals for the estimated GM boundaries were estimated as the nutrient concentrations corresponding to the upper and lower 95% confidence limits for the binomial regression lines at the chosen cutoff p value (see Fig. 2). All statistical analyses were performed in R Studio program for Statistical computing (R Core Team, 2024), applying the modEvA package (Barbosa et al., 2013) for evaluation of the binomial model fits.

The BLR-derived estimated regional nutrient boundaries were compared with other estimates derived from linear regression methods and common metrics (Poikane et al., 2021; Poikane et al., 2022).

2.3. Climate data

Data on air temperature (°C) and precipitation (mm) was obtained from daily gridded observational datasets derived from *E*-OBS and available through Copernicus (copernicus.eu). These climate data are structured on regular grids with spatial resolutions of 0.1 and 0.25 degrees in latitude and longitude. The climate data were aligned with the sampling locations for nEQR and nutrients (Fig. 1), and site-specific daily mean air temperature and total precipitation values were extracted for each sampling site for the years with nEQR- and nutrient data. For instance, if nEQR and nutrient data were available for a specific location in 2010, 2012 and 2013, we extracted daily climate data for

Table 1

Number of water bodies (WBs) in the data set used for estimating good/moderate (GM) boundaries for total phosphorus (TP) and total nitrogen (TN) for the different lake (L)- and river (R) types in the Nordic (top) and Central-Baltic region (bottom). Only IC types that had adequate data and sufficiently strong relationships between nEQR and nutrients to allow statistical boundary estimation are shown. The type-code refers to the intercalibrated type*, along with a short type name referring to alkalinity (alk.: low, moderate (mod) or high) and humic content (clear or humic). BQE is the biological quality element used to estimate the GM boundaries for the two nutrient parameters.

Nordic	Type code	Type name*	Nutrient	WBs (total)	WBs Norway	WBs Sweden	WBs Finland	BQE
Lakes	L-N1	Mod alk. Clear	TP	63	40	23	na	Phytoplankton
			TN	63	40	23	na	
	L-N2a	Low alk. Clear	TP	394	66	23	305	Phytoplankton
			TN	394	66	23	305	
	L-N3a	Low alk. Humic	TP	453	53	66	334	Phytoplankton
			TN	453	53	66	334	
	L-N8a	Mod alk. Humic	TP	110	38	72	na	Phytoplankton
			TN	109	37	72	na	
Rivers	R-N1	Mod alk. Clear	TP	143	107	3	33	Phytobenthos
			TN	133	97	3	33	
	R-N3	Low alk. Humic	TP	442	116	151	175	Phytobenthos
			TN	420	94	151	175	
	R-N4	Mod alk. Humic	TP	96	7	7	82	Phytobenthos
			TN	95	6	7	82	
Central-Baltic	Type code	Type name*	Nutrient	WBs (total)	Denmark	Latvia	Poland	BQE nEQR matching
Lakes	L-CB1	High alk. Clear, shallow	TP	678	12	179	487	Phytoplankton
			TN	695	12	179	504	
	L-CB2	High alk. Clear, very shallow	TP	230	18	57	155	Phytoplankton
			TN	229	18	57	154	
Rivers	R-C4	Medium-mod-high alk.	TP	592	99	46	447	Phytobenthos
			TN	607	99	46	462	
	R-C5	Large, mod-high alk.	TP	164	na	41	123	Phytobenthos
			TN	164	na	41	123	

[*] Type names are fully described in Supporting Material, Section 3, see also EC, 2024.

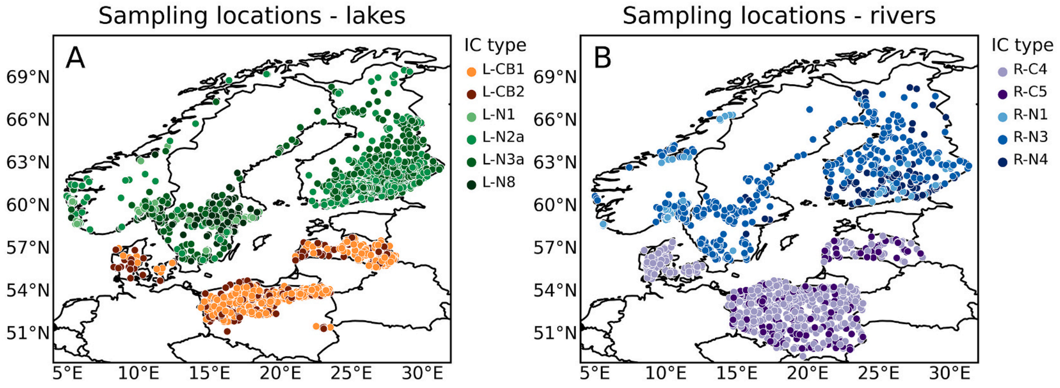


Fig. 1. Sampling locations for lakes (A) and rivers (B) with the point colours representing the different IC types.

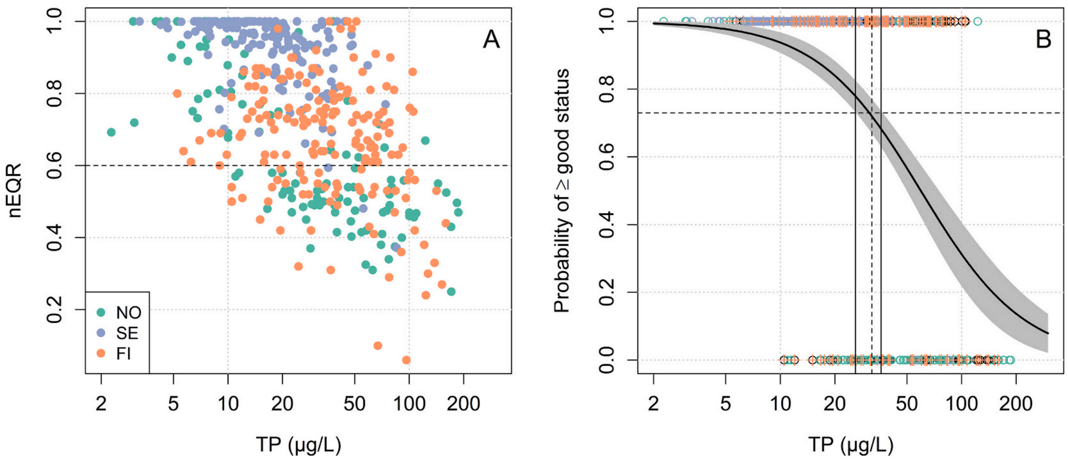


Fig. 2. Example of the binomial logistic regression (BLR) approach applied on data from IC type R-N3 (Low alkalinity, humic rivers in the Nordic region). A) Plot of nEQR vs. log(TP) (µg/L) on linear scale, with data from Norway (NO), Sweden (SE) and Finland (FI). The horizonal line marks the boundary between moderate and good status (nEQR = 0.6). B) Plot of the likelihood of good or better status after transformation of the same data to binary values of 1 (nEQR >0.6, i.e. good or better status) or 0 (nEQR ≤0.6, i.e. moderate or worse status). The thick black curve is the BLR regression line, with a 95% confidence interval marked in grey. The horizontal dotted line represents the probability of good status giving a balanced rate of misclassifications (= the cutoff p value, see Suppl. Mat. Section 4). The vertical dotted line indicates the estimated GM boundary for TP, while the thin solid lines are the 95% confidence interval of the estimated boundary.

those three years.

Based on the site-specific daily time series, we calculated three climate features representing the temperature and rainfall conditions during summer for each site and year. These were 1) mean air temperature (C); 2) total precipitation (mm); and 3) variability in precipitation. The latter was calculated as the coefficient of variation (CV value), i.e. the standard deviation of daily precipitation divided by the mean daily precipitation. High CV values represent uneven distribution of precipitation, with most precipitation coming from large rain events. We used data from June, July and August for temperature, since we wanted temperature to represent the warmest quarter of the year. For precipitation, we used the period May – September, since we also wanted to include rainfall occurring late spring and early autumn, which may influence both nutrient runoff and water levels/flow rates during the growing season.

2.4. Climate impact analysis

To assess the reltionships between nEQR and climate variables, while accounting for effects of TP and broad spatial patterns, we used an approach inspired by Heuschele et al. (2023). This applied generalized additive models (GAMs, using the mgcv package (Wood, 2011) in R) to allow for non-linear effects, and a deviance analysis to partition the variance between climate variables (mean air temperature, sum of precipitation and CV value for precipitation; see section on climate data), TP and spatial variables (latitude and longitude). TP and sum of precipitation were log transformed to increase normality. The whole analysis was run for groups of IC types expected to have similar background concentrations of TP (Table 2). In lakes, the response variable was phytoplankton nEQR; in rivers phytobenthos nEQR.

Table 2
Overview of data sets used for climate analysis. IC types and description show the types that were grouped for analysis. The number of WBs is the number of unique water bodies in the group, while number of WB years is the number of unique years of data for all water bodies (i.e., several WBs had data from more than one year).

IC types	Description	Number of WBs	Number of WB years
L-N3a and L-N8	Nordic humic lakes	616	2462
L-N1 and L-N2a	Nordic clear lakes	464	1584
L-CB1	Central Baltic stratified lakes	677	701
L-CB2	Central Baltic non-stratified lakes	228	237
R-N1, R-N2 and R-N4	Nordic clear rivers	237	367
R-N3	Nordic humic rivers	400	1020
R-C4 and R-C5	Central-Baltic medium/large rivers	520	603

The statistical analysis involved the following steps: First, we randomly divided the data into a training dataset containing 70% of the observations, and a test dataset containing 30% of the observations. To determine the effects of the climate variables relative to latitude/longitude and TP, we fitted four GAMs (using family = "Gaussian") to the training dataset: 1) A null model (m_{NULL}) only containing the intercept; 2) a model with spatial effects (latitude and longitude) and TP (m_{SPAT_TP}); 3) a model with climate variables (m_{CLIM}); and 4) a model with all factors (m_{FULL}). Latitude and longitude were included in the GAM as tensor smoothing products (Wood, 2006). For nEQR and TP, yearly mean values per WB were used, along with climate data for the corresponding years. To account for varying number of years (n) per WB, we weighted each observation by 1/n using the "weights" argument in the gam() function in the mgcv package (Wood, 2011). Based on the deviances (a measure of how well the model fits the data) from the gam models 1–4, we followed the principles in Heuschele et al. (2023) and calculated the proportion (Prop) of deviance explained by latitude/longitude and TP as $Prop_{SPAT\_TP} = [deviance(m_{CLIM}) - deviance(m_{FULL})]/deviance(m_{NULL})$; by climate as $Prop_{CLIM} = [deviance(m_{SPAT\_TP}) - deviance(m_{FULL})]/deviance(m_{NULL})$; and by all factors as $Prop_{ALL} = 1 - deviance(m_{FULL})/deviance(m_{NULL})$. The unassignable variance was calculated as $Prop_{ALL}$ - ($Prop_{SPAT\_TP} + Prop_{CLIM}$)). To estimate the predictive power of the best model (which was always m_{FULL}), we used the model fitted to the training dataset to predict nEQR in the test dataset and estimated R^2 for the linear relationship between predicted and observed nEQR. As the analysis was based on sampling random training and test datasets, we repeated the whole procedure 1000 times and calculated the mean proportions of deviances and mean R^2 for all iterations. We also calculated average parameter estimates and *p*-values for each predictor based on the 1000 iterations. To visualize the individual effects of significant explanatory variables ($p < 0.05$), we used the full model to predict nEQR over the range of values for each of the explanatory variables. The remaining explanatory variables were set to their mean values.

3. Results

3.1. Estimated nutrient boundaries supporting good ecological status

The estimated GM boundaries for both TP and TN are generally lower in the Nordic region than in the Central-Baltic region (Fig. 3 and Tables **S.6-S.13**). For Nordic lakes, the estimated GM boundary values for TP range from 14 to 24 µg/L for the different types, while the TN boundaries range from 428 to 689 µg/L. The lowest TP boundary values were estimated for low alkalinity clear lakes (L-N2a) and moderate alkalinity clear lakes (*L*−N1), while the lowest TN boundaries were

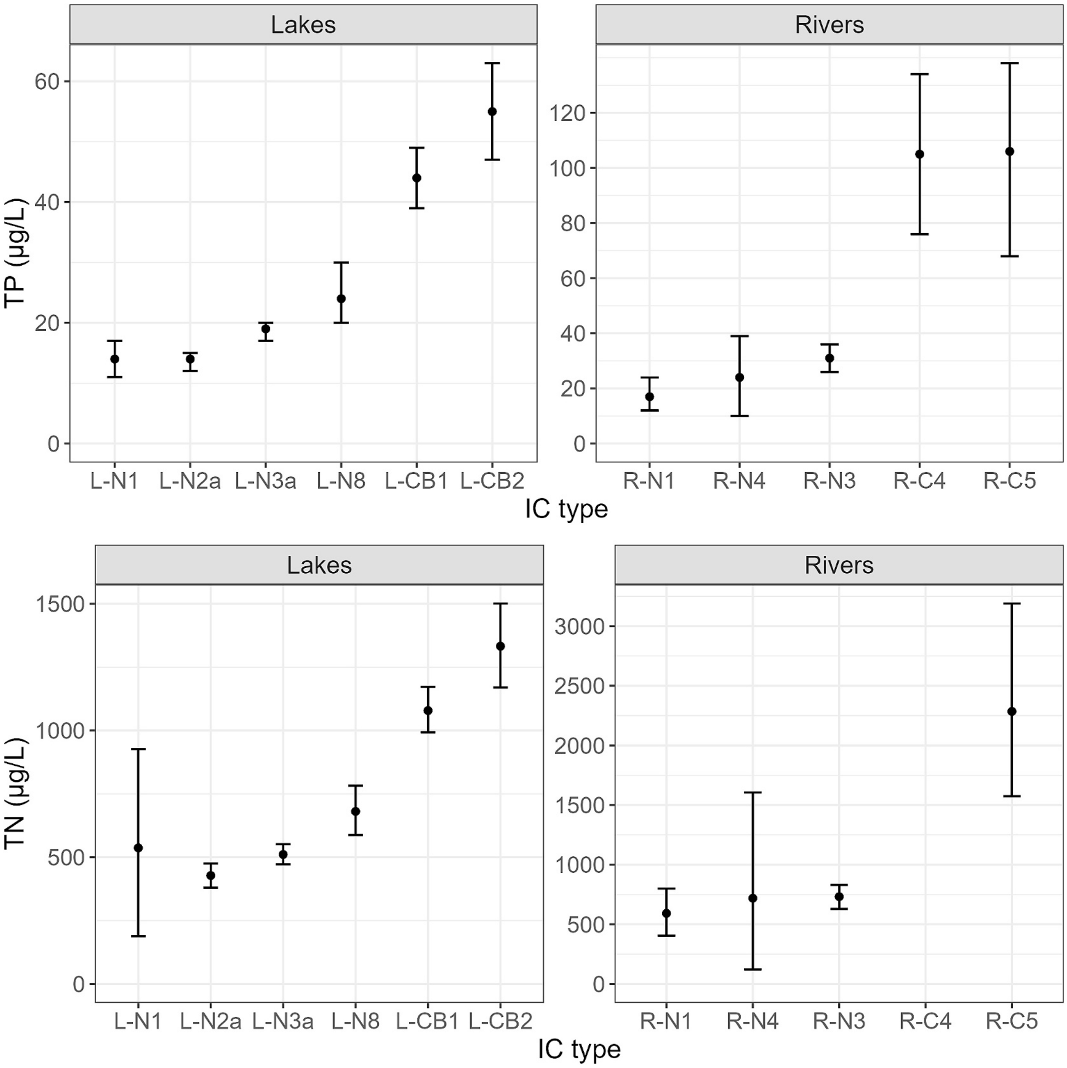


Fig. 3. Estimated GM boundary values (black points) and their 95% confidence intervals (vertical bars) for TP (total phosphorus; µg/L) and TN (total nitrogen; µg/L) in different intercalibrated common (IC) types of lakes (left panels) and rivers (right panels) in the Nordic (N) and Central Baltic (CB/C) regions.

estimated for low alkalinity clear (L-N2a) and humic (L-N3a) lakes. The TN estimate in moderate alkalinity clear lakes (L-N1) was in the same range, but with high uncertainty. Moderate alkalinity, humic lakes (L-N8a) had the highest estimated boundaries for both TP and TN.

For Nordic rivers, the estimated GM boundary values for TP range from 17 to 31 μg/L, with the lowest values in moderate alkalinity non-humic small (R-N1) and medium (R-N4) rivers and the highest values for low alkalinity humic rivers (R-N3). The GM boundary values for TN in Nordic rivers range from 592 to 732 μg/L for three IC types (R-N1, R-N3 and R-N4). The confidence intervals for both TP and TN were quite narrow for all the types, except for TN in R-N4.

For Central-Baltic lakes, the estimated TP boundaries range from 44 to 55 μg/L, while the TN boundaries range from 1079 to 1333 μg/L. The stratified lakes (L-CB1) have clearly lower boundaries than the very shallow, unstratified lakes (L-CB2).

For Central-Baltic rivers, the estimated TP boundaries are 105 and 106 μg/L for the two high alkalinity types (R-C4 and R-C5). The TN boundary is close to 2300 μg/L for the only river type that could be estimated with the available datasets (R-C5). The confidence intervals for both TP and TN in Central Baltic rivers are wide.

3.2. *Comparison of current national boundaries with the regional estimated boundaries*

The relationship between the estimated GM boundaries (Fig. 3) and the current boundaries used by the countries who provided data in the Nordic and Central-Baltic regions, shows that most of the current boundaries are within the confidence intervals of the estimated boundaries (Fig. 4 and Fig. 5, details in Tables **S.6-S.13**). For some countries and IC types, however, the currently used boundaries are higher than the upper 95% confidence limit of the estimated boundaries, indicating that they may not support good status for nutrient sensitive biological quality elements. For TP in the Nordic region, the current GM boundaries in the Finnish lake types L-N1 and L-N3a (Fig. 4**A**, Table **S.6**) and the river types R-N1 and R-N3 (Fig. 4**C**, Table **S.8**) are higher than the upper 95% confidence interval of the estimated boundaries. The current Norwegian GM boundaries for moderate alkalinity, clear lakes (L-N1: 17 μg/L) and rivers (R-N1: 25 μg/L) are also equal to or slightly higher than the upper 95% confidence limit of the estimated values (see Tables **S.6** and **S.8**).

Among the Central-Baltic countries (Fig. 5), the current Polish GM boundary range for TP in lake type L-CB1 (50–60 μg/L) is higher than

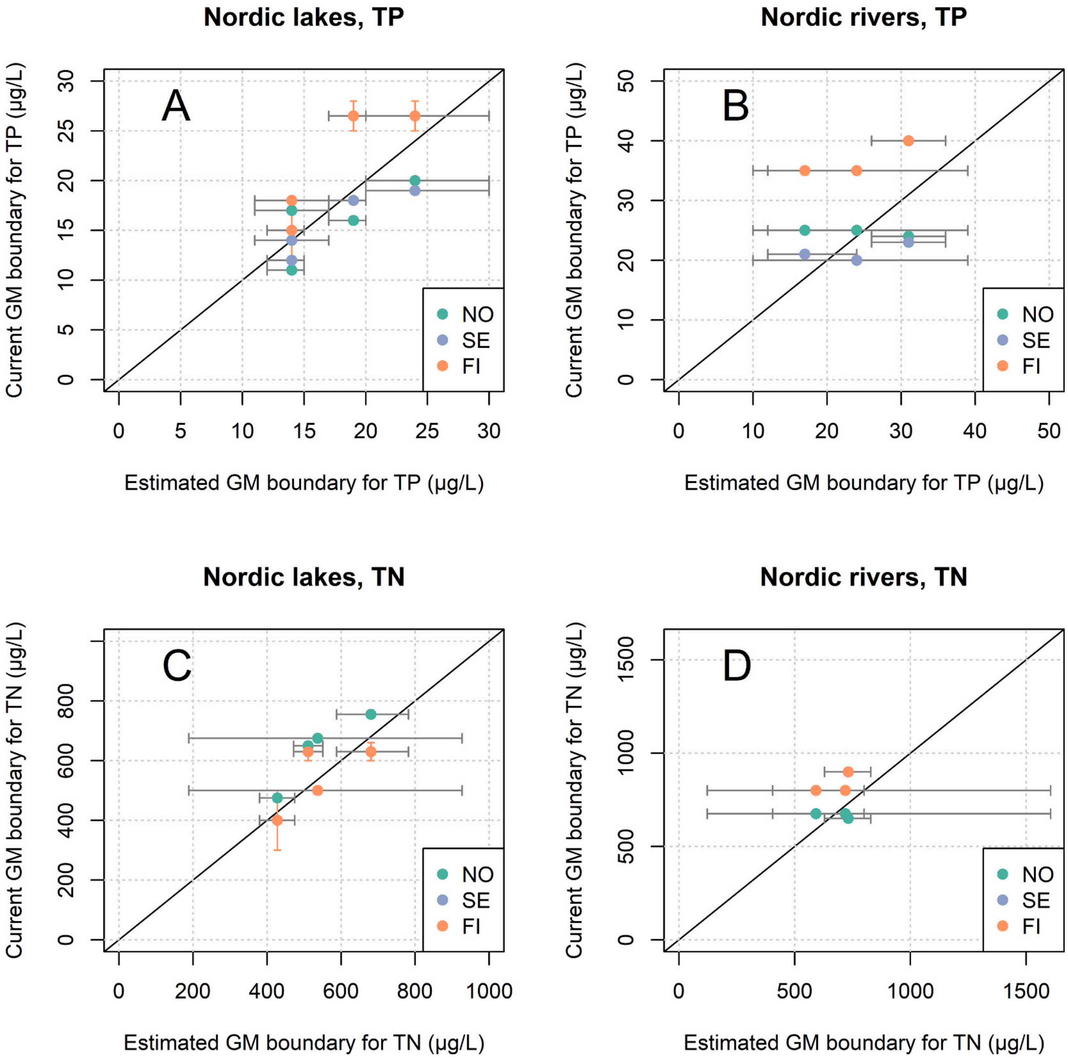


Fig. 4. Relationship between currently used national GM boundary values (y-axis) and estimated GM boundary values (x-axis) using BLR for TP (total phosphorus; μg/L) and TN (total nitrogen; μg/L) for the same intercalibration types as given in Fig. 3 for lakes and rivers in the Nordic region. A) TP in Nordic lakes; B) TN in Nordic lakes; C) TP in Nordic rivers; and D) TN in Nordic rivers. The black line indicates the 1:1 line. Horizonal bars indicate the 95% confidence interval for the estimated boundaries from the BLR regression. Vertical bars indicate the range of current national boundaries for the IC types that may include several national types. NO = Norway; SE = Sweden; FI = Finland. See section 5a in the Supplementary Information for more details.

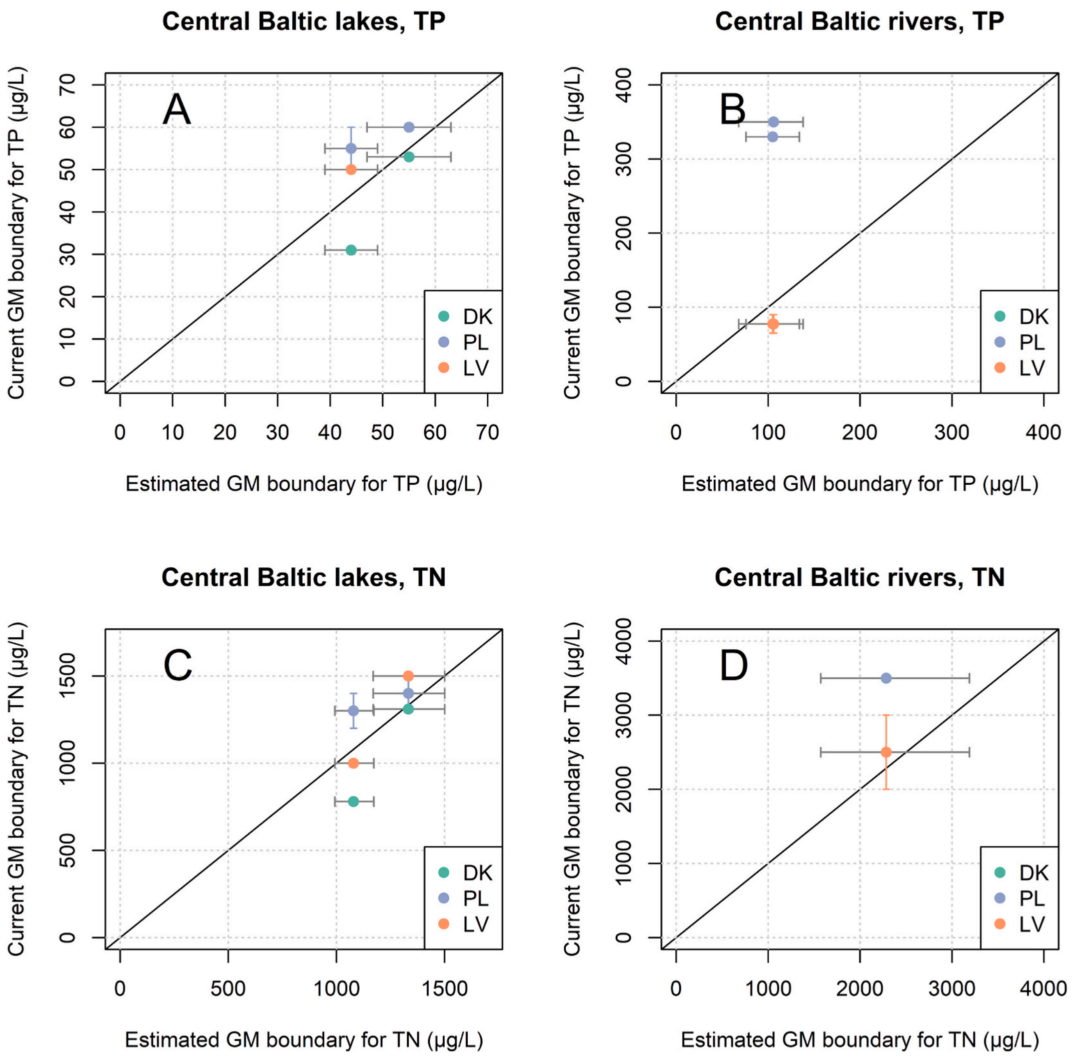


Fig. 5. Relationship between currently used national GM boundary values (y-axis) and estimated GM boundary values (x-axis) using BLR for TP (total phosphorus; µg/L) and TN (total nitrogen; µg/L) for the same intercalibration types as given in Fig. 3 for lakes and rivers in the Central-Baltic (CB) region. A) TP in CB lakes; B) TN in CB lakes; C) TP in CB rivers; and D) TN in CB rivers. The black line indicates the 1:1 line. Horizonal bars indicate the 95% confidence interval for the estimated boundaries from the BLR regression. Vertical bars indicate the range of current boundaries for the IC types that are comprised of several national types. DK = Denmark; PL = Poland; LV = Latvia. See section 5a in the Supplementary Information for more details.

the upper 95% confidence limit (49 µg/L; Fig. 5**A**, Table **S.10**). The current Polish river boundaries for TP are two to three times higher than the upper 95% confidence limit of the estimated boundaries (Fig. 5**C**; Table **S.12**). The Latvian GM boundary for L-CB1 was only slightly higher (50 µg/L) than the estimated upper limit of the 95% confidence interval (49 µg/L) (Fig. 5**A**, Table **S.10**). Denmark has not set any TP boundaries for rivers.

For TN in Nordic lakes, the currently used boundaries for lake type L-N3a in Norway (650 µg/L) and Finland (600–660 µg/L) are higher than the upper 95% confidence limit for the estimated boundary (551 µg/L; Fig. 4**B**; Table **S.7**). Current TN boundaries in Finland and Norway are also in the upper range of the estimated boundaries for lake type L-N2a (Table **S.7**). Sweden has not set any boundaries for TN in lakes. In Nordic rivers, the current Finnish TN boundary for R-N3 (low alkalinity, humic rivers) is higher than the upper 95% confidence limit for the estimated boundary, while the boundary for R-N1 is the same as the upper 95% confidence limit for the estimated boundary (Fig. 4**D**; Table **S.9**).

Among the Central-Baltic countries, the Polish boundary range reported for TN in lake type L-CB1 is higher than the estimated upper 95% limit (Fig. 5**B**; Table **S.11**). The Polish boundary for TN in river type R-C5 is also higher than the estimated upper 95% limit (Fig. 5**D**; Table **S.13**). Denmark has not set any TN boundaries for rivers (although they have boundaries for the TN loads to the sea).

3.3. *Climate impacts on nEQR values*

The full GAM model with both TP, climate, and spatial variables (latitude and longitude) explained 38–63% of the variation in phytoplankton nEQR (as judged by the R^2 for the linear relationship between observed and predicted nEQR in the test data set; see methods) in the four groups of lake types (Fig. 6; Table **S.14**). The fraction of deviance explained by climate variables alone was quite small, ranging from 1.3 to 6% (Fig. 6). TP and latitude/longitude together explained most of the deviance (28–55%; Fig. 6), mostly driven by the strong negative relationship between TP and nEQR (Fig. 7**A, C, E, G**). Between 3 and 10% of the deviance in nEQR could not be separated between climate and the other variables, likely due to co-variation between the latitude, longitude and climate.

Even though the fraction of deviance explained by climate was low, there were significant effects ($p < 0,05$) of mean summer (June–August) air temperature on phytoplankton nEQR in three out of four type-groups of lakes (Table **S.14**; Fig. 7). In Nordic, humic lakes (L-N3 and L-N8)

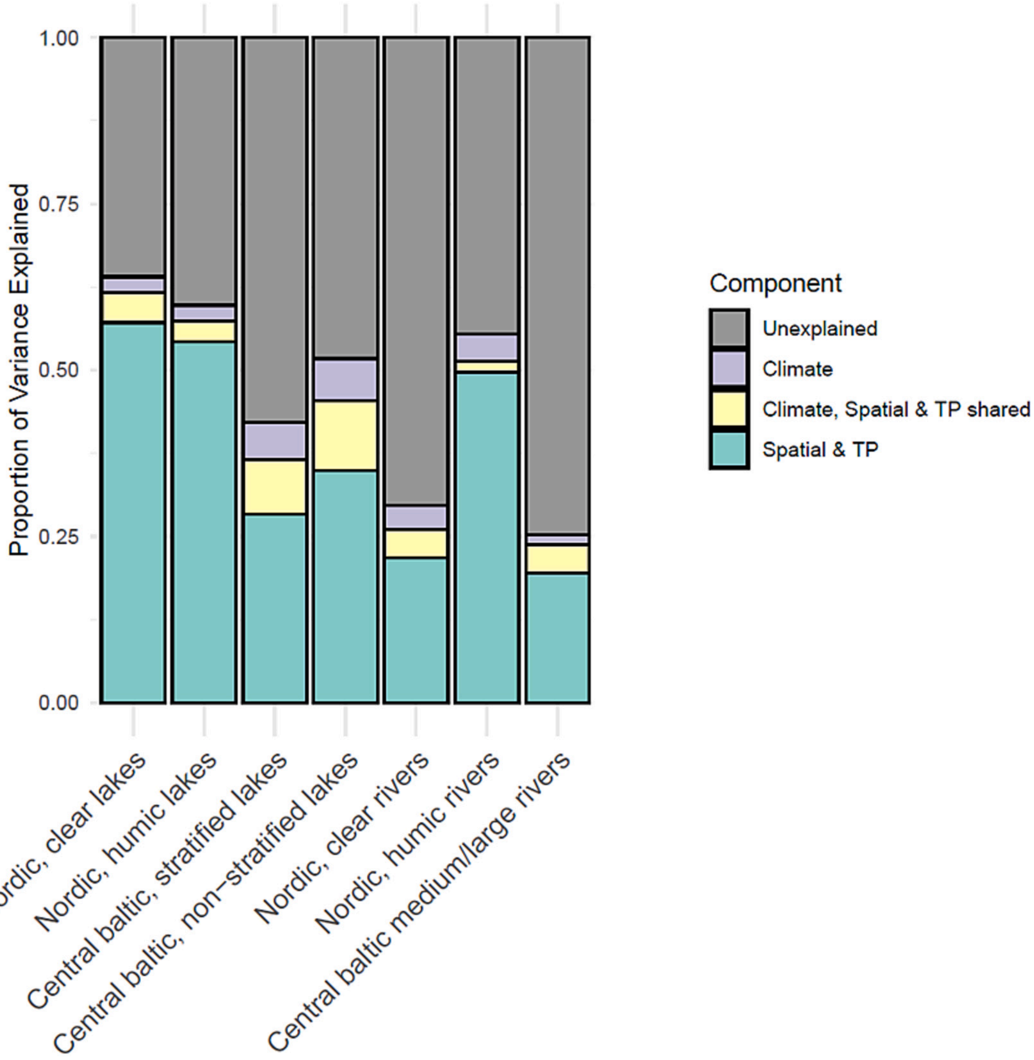


Fig. 6. Fraction of deviance in nEQR explained by different model components for the four groups of lake types (Nordic clear lakes [IC type L-N1 and L-N2a]; Nordic humic lakes [IC type L-N3 and L-N8]; Central-Baltic stratified lakes [IC type L-CB1]; and Central-Baltic non-stratified lakes [IC type L-CB2]) and river types (Nordic clear rivers [IC type R-N1 and R-N4]; Nordic humic rivers [IC type R-N3]; Central-Baltic medium/large rivers [R-C4 and R-C5]). The green portion of each bar represents the deviance explained by total phosphorus (TP) and spatial factors (latitude and longitude). The violet portion represents the variance explained by climate variables (mean June – August temperature, total precipitation and variability in precipitation (CV value) from May to September). The yellow portion indicates the fraction of variance shared between climate, and spatial and TP. The grey portion represents the unexplained variance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(Fig. 7**D**) and Central-Baltic stratified lakes (L-CB1; Fig. 7**F**), the temperature effect was negative. In Nordic, clear lakes (Fig. 7**B**), the temperature effect was more unimodal. There was also a slight tendency for a negative effect in the Central-Baltic non-stratified lakes (L-CB2; Fig. 7**H**), but the effect was not statistically significant ($p = 0.15$). Neither the sum of precipitation nor the CV value for precipitation were significantly related to nEQR in lakes (Table **S.14**).

For rivers, the fraction of explained variance in nEQR was lower than for lakes, with nEQR mainly being related to TP and spatial patterns (Fig. 6; Table **S.15**). No significant effects were found for air temperature in any of the river types. However, for precipitation, we found significant effects in both the Nordic river types: In Nordic, humic rivers (R-N3), the effect of total precipitation from May to September was slightly negative (Fig. 8). For Nordic clear rivers (R-N1 and R-N4), only the variability in precipitation (CV value) was significant, showing a unimodal relationship with a clear positive effect from low to intermediate variability and a clear negative effect from intermediate to high variability.

4. Discussion

4.1. Safe ecological boundaries

4.1.1. Uncertainties in estimated GM boundaries

The estimated boundaries for TP in the Central-Baltic (CB) types of both lakes and rivers have wider confidence intervals than the Nordic types (Fig. 3), indicating higher uncertainty in the estimated boundaries for the CB types. Generally, the confidence intervals are wider for the CB river types than for lake types in the same region (Fig. 3). High uncertainties are partly due to unbalanced datasets with relatively little data available from the lower part of the nutrient gradients (oligotrophic sites). This was especially evident for the CB river types (SI figs. 31–33), where a large majority of the WBs had TP concentrations >50 µg P/L. In Polish rivers, most TP concentrations were > 100 µg P/l (SI figs. 31–33). In this range, phosphorus is expected to be in excess relative to other growth limiting factors, and ecological responses to increasing phosphorus concentrations above 100 µg P/L are expected to be small both with respect to species composition and biomass (Charles et al., 2019).

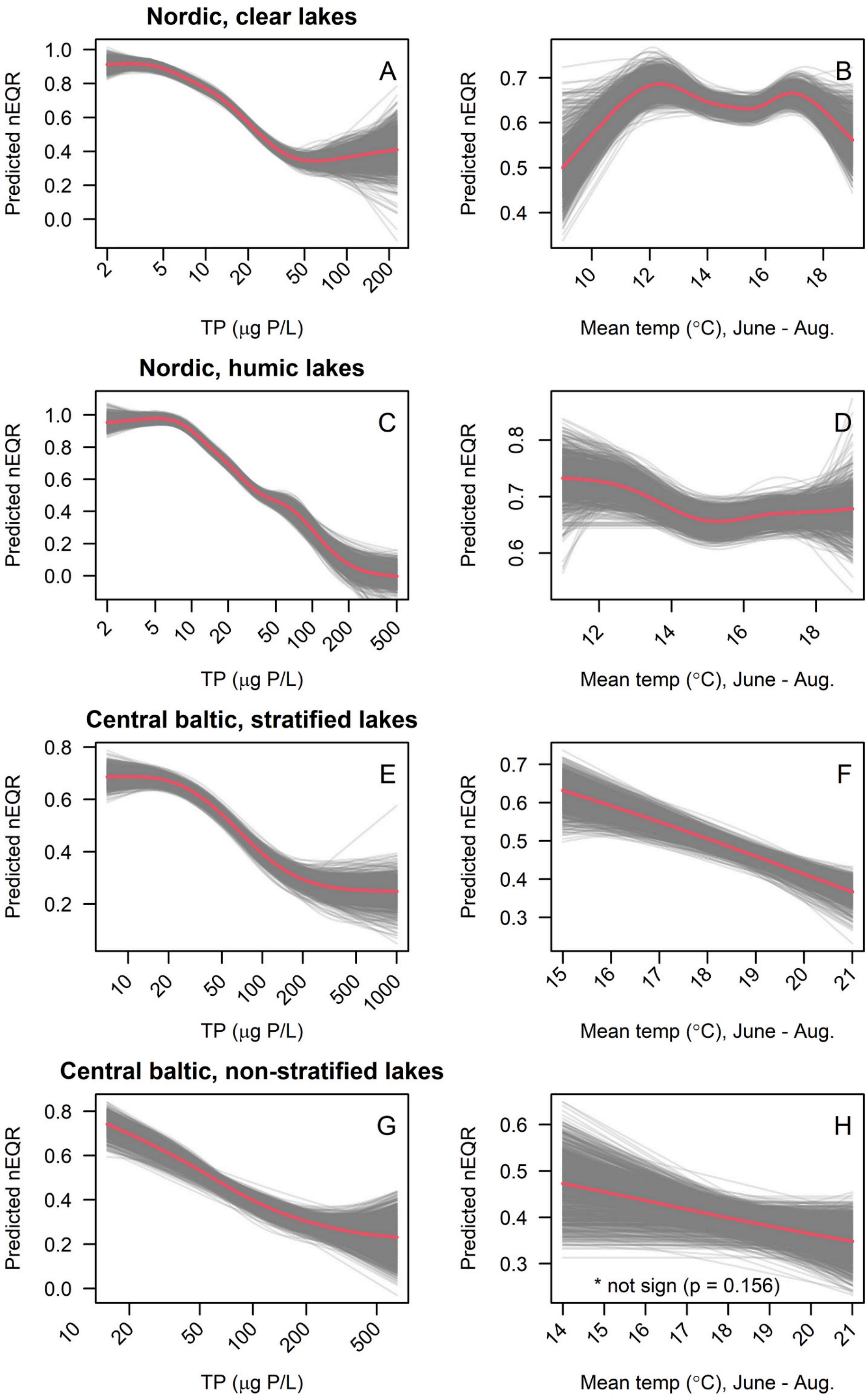


Fig. 7. Predicted effects of total phosphorus (TP, µg/L) and mean June – August temperature (°C) on phytoplankton nEQR in four groups of lakes. A) and B) Nordic clear lakes (IC type L-N1 and L-N2a); C) and D) Nordic, humic lakes (IC type L-N3 and L-N8); E) and F) Central-Baltic, stratified lakes (IC type L-CB1); and G) and H) Central-Baltic non-stratified lakes (IC type L-CB2) Faint grey lines represent predictions from 1000 model iterations, where the red line represents the mean of all predictions. When predicting single effects, other predictors were set to their mean value. Detailed results from the modelling (*p*-values, R^2 and estimated degrees of freedom) are given in table S.14. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Another reason for the larger uncertainty in the CB region than in the Nordic region can be that the CB types are wider and more heterogenous, not taking humic content into account. Moreover, some national biological metrics respond less well to nutrients, e.g. the saprobic diatom indices used for assessing ecological status of phytobenthos in rivers in Denmark and Poland, which are used together with a trophic index for diatoms. The Latvian metric is the IPS index, which responds to both nutrients and organic pollution (Table **S.1**). Sweden also uses the IPS index but has recently developed a more precise diatom index responding to phosphorus (PDISE) (Kahlert et al., 2023).

The large uncertainties for TN, e.g. for IC type L-N1 and R-N4 (Fig. 3), are likely caused by the overall lower correlations between

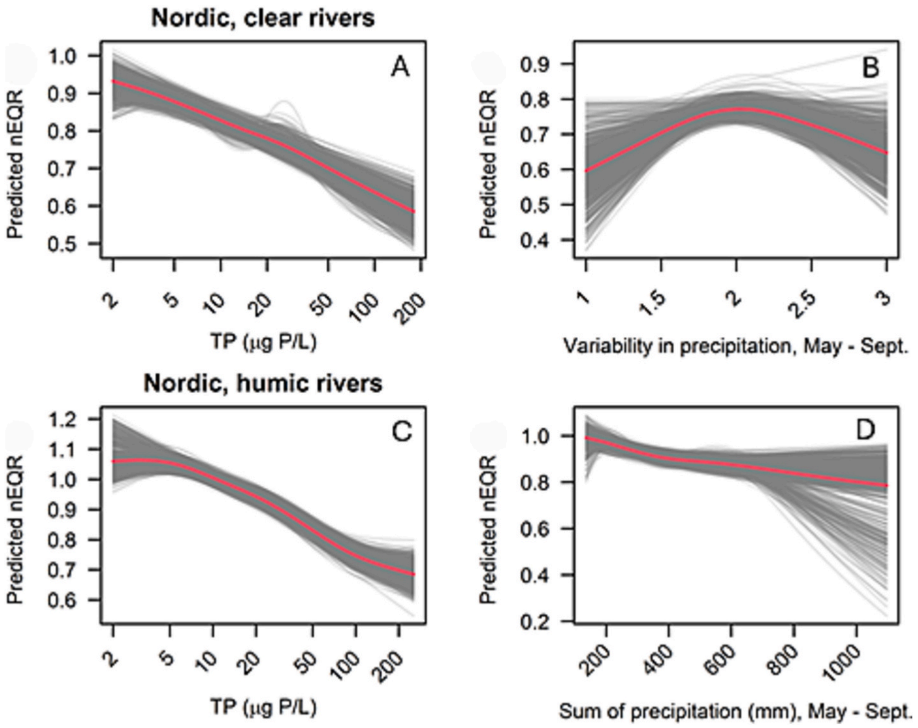


Fig. 8. Predicted effects of total phosphorus (TP, µg/L) and significant precipitation variables for two groups of Nordic river types. A) and B) Nordic clear rivers (IC type R-N1 and R-N4); and C) and D) Nordic humic rivers (IC type R-N3). Faint grey lines represent predictions from 1000 model iterations, where the red line represents the mean of these predictions. When predicting single effects, other predictors were set to their mean value. Detailed results from the modelling (p-values, R^2 and estimated degrees of freedom) are given in table S.15. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

nEQR and TN compared to TP for both phytoplankton and phytobenthos. This has also been observed in other analyses of European monitoring data (Poikane et al., 2022) and is likely explained by the predominant P limitation of freshwaters (e.g. Schindler et al., 2016). Moreover, most indices for phytoplankton (e.g. Phillips et al., 2013) and phytobenthos (e.g. Schneider and Lindstrøm, 2011; Charles et al., 2019) are designed based on species optima for phosphorus. Significant relationships between TN and nEQR for phytoplankton/phytobenthos are often found, however, but are more likely to be a result of the co-variation between N and P in nutrient supply (Downing and McCauley, 1992). Nonetheless, reduction in summer nitrogen concentrations has shown to be an effective control on phytoplankton biomass, including cyanobacteria, over a 37-year time-series (Shatwell and Köhler, 2019). Thus, setting reasonable GM-boundaries for TN may be important to reduce cyanobacteria blooms.

Finally, there are other confounding factors that influence the phytoplankton and phytobenthos responses to nutrients, e.g. pesticides or influx of inorganic particles from the catchments causing poor underwater light climate. It may be hypothesized that these factors are more pronounced in the Central-Baltic than in the Nordic region, due to more agricultural land and higher population density. Rivers are also likely to have more of these multiple pressures than lakes (Birk et al., 2020; Spears et al., 2021), as rivers have much larger variation in flow and turbidity than lakes, which have longer retention times, allowing particles to settle more efficiently. Potentially, this may cause larger variability in the nEQR vs. nutrient relationships in rivers, compared to lakes. Interactions between phytoplankton and macrophytes, as well as grazing by zooplankton in lakes and by benthic invertebrates in rivers also contributes to the variability of the relationships between nutrients and the phytoplankton or phytobenthos (Jeppesen et al., 1999; Scheffer et al., 1993; Atkinson et al., 2016; Hall et al., 2003; Hill and Griffiths, 2017), and these biological interactions are more important when more nutrients are available than when nutrients are strongly limiting.

Similarities/differences of nutrient boundaries given by other papers.

The estimated boundaries for lakes based on the BLR method are highly correlated ($r^2 = 0.98$ for both TP and TN) with those estimated by Poikane et al. (2021 and 2022) with linear regression (Table 3). The exceptions for TP boundaries in lakes are the Nordic clear lakes with low or moderate alkalinity (L-N1 and L-N2a), where the GM boundaries estimated with the BLR approach are lower (more stringent) than those estimated by Poikane et al. (2022). For TN, the BLR estimate is more stringent than the linear regression estimate for the humic lake types L-N3 and L-N8 but quite in line for the other lake types (L-N1, L-CB1, L-CB2). A possible reason for this discrepancy for the humic lakes can be that the datasets are different. Another reason can be that the regression with TN has a higher proportion of mismatches than what is shown for TP, and that the linear regression is inferior to the BLR regression to account for such mismatches.

For rivers, the comparison between the BLR-derived GM estimates for TP and those derived by linear regression is more difficult, since Poikane et al. (2021) used soluble reactive phosphorus (SRP) and not TP as the nutrient variable. Moreover, they used other common IC types for the linear regressions (R-C1 and R-C3) than the types used in this paper (R-C4, R-C5). There were also no Nordic types included. However, the literature survey provided by Poikane et al. (2021) in their table 9, suggests a GM boundary for TP from 30 to 60 µg/L for rivers in general. This boundary range is supported by Charles et al. (2019) who found that the TP boundary should be lower than 50 µg/L based on diatoms in a set of US rivers. The boundaries estimated for Central-Baltic rivers are higher than that range (87–106 µg/L; Table **S.12**), while the boundaries estimated for the Nordic river types are lower (17–45 µg/L; Table **S.8**). The GM boundary for TN for the Central Baltic river type R-C5 is 2.3 mg/L (Table **S.13**), which corresponds well with the range derived by Poikane et al. (2021) for other Central Baltic types (1–3.5 mg/L). Other papers referred to by Poikane et al. (2021) provide a TN range from 0.5

Table 3

Comparison of GM boundaries for total phosphorus (TP) and total nitrogen (TN) for European lake types derived with binomial logistic regressions (BLR) versus those derived with linear regression (LR) reported by Poikane et al., 2022. Values are in µg/L. The cells with “na” mean that estimates are not available.

			This paper (BLR)		Poikane et al., 2022 (LR)	
Region	Type	Parameter	GM estimate	GM 95% Conf interval	GM estimate	GM 25th–75th quartiles
Central Baltic	L-CB1	TP	44	39–49	39	28–55
Central Baltic	L-CB2	TP	55	47–63	52	37–66
Nordic	L-N1	TP	14	11–17	18	16–22
Nordic	L-N2a	TP	14	12–15	20	15–26
Nordic	L-N2b	TP	na	na	14	10–18
Nordic	L-N3	TP	19	17–20	22	18–27
Nordic	L-N8	TP	24	20–30	27	23–33
Central Baltic	L-CB1	TN	1079	993–1173	1110	790–1570
Central Baltic	L-CB2	TN	1333	1170–1501	1320	1060–1540
Nordic	L-N1	TN	537	189–927	650	540–820
Nordic	L-N2a	TN	428	380–475	na	na
Nordic	L-N2b	TN	na	na	na	na
Nordic	L-N3	TN	511	472–551	710	620–830
Nordic	L-N8	TN	689	599–793	860	710–1050

to 2 mg/L which covers the BLR-derived GM boundaries for the Nordic river types (Table **S.9**).

Interpretation of mismatches between currently used national boundaries and the estimated boundaries for comparable types of water bodies.

Most of the currently used nutrient boundaries are found to be in line with the estimated boundaries or at least within the 95% confidence interval for the estimated boundaries. However, some of the current Finnish boundaries were found to be higher than this for several types of lakes and rivers (Fig. 4, Tables **S.6** & **S.8**). The majority of the data used for the estimation of safe ecological boundaries for phosphorus in low alkalinity lakes in the Nordic region was from Finnish water bodies (77% for the clear L-N2a lakes and 74% for the humic L-N3a lakes), indicating that the results are indeed representative for Finnish conditions. Thus, the current Finnish boundaries for the mesohumic L-N3a lakes seem too high to support good status for phytoplankton. This implies that the Finnish TP boundaries in mesohumic Finnish lakes may need to be reconsidered.

However, Finland naturally has higher concentrations of humic substances than Norway and Sweden, within otherwise comparable types of lakes and rivers, due to higher forest and bog cover (Crapart et al., 2023). More humic waters can justify higher phosphorus boundaries since a higher fraction of the total phosphorus is bound to by relatively recalcitrant humic, organic matter (Jones, 1992; Kortelainen, 1993; McKnight, 2001). Moreover, humic substances in lakes can cause light limitation, thereby reducing phytoplankton resource use efficiency and sensitivity to phosphorus (Effler et al., 1985; Lyche Solheim et al., 2024; Seekell et al., 2015). Both these mechanisms can cause lower phytoplankton biomass, and thus higher nEQR, per unit of TP. There were in fact higher concentrations of humic substances (as measured by color) in the Finnish lake water bodies (median color [Q1-Q3]: 72 [56–95] mg Pt/L) than in the Norwegian (42 [32–68] mg Pt/L) and Swedish (51 [46–76] mg Pt/L) lake water bodies within the Nordic humic types included in the joint dataset, which may justify the higher TP boundaries used in Finland compared to those estimated for the combined dataset.

The impacts of humic substances on TP concentration and light climate can also explain why GM boundaries for TP may be higher in mesohumic waterbodies than in oligohumic water bodies within comparable ranges of alkalinity (Fig. 3; details in Table **S6** and Table **S7**). This result is also supported by a study of >2000 Finnish lakes (Vuorio et al., 2020), who found that threshold values for TP needed to avoid cyanobacterial blooms were lower in oligohumic (water color <30 mg Pt/L) than in mesohumic (water color 30–90 mg Pt/L) lakes.

The current Polish boundaries for TP in all the common river types included in this paper were highly above the 95% confidence interval of the estimated boundaries (Fig. **5C**, Table **S.12**) and slightly above this limit for the L-CB1 lakes (Fig. **5a**, Table **S10**). This may be due to using other methods than modelling or regression to set the current national nutrient boundaries, e.g. distribution of classified water bodies or expert judgement (Poikane et al., 2019). Polish data dominated the Central-Baltic dataset, contributing 67% of the lakes data and 72–76% of the rivers data (Table **1**), indicating that the results are indeed representative for Polish conditions. For the rivers, the BLR results are quite uncertain, as illustrated with the wide confidence intervals (Fig. **5C**), indicating that the Polish phytobenthos metric is on weakly responding to TP. One reason is that the Polish phytobenthos method is not a pure trophic index (focusing on nutrients only) but a multimetric index including a Trophic index, Saprobic index and Reference index – responding to nutrients, organic pollution and other pressures (Picinska-Faltynowicz, 2009; Poikane et al., 2016). Another reason could be a confounding influence of alkalinity, as phytobenthos changes across gradients of both nutrients and alkalinity (Baattrup-Pedersen et al., 2022).

5. Climate impacts on nEQR-values

5.1. *Interpretation of results and comparison with other papers*

After accounting for concentration of TP and broad spatial patterns (latitude and longitude), the fraction of variance in nEQR explained by climate variables was relatively small. Still, nEQR-values for phytoplankton were negatively related to air temperature in three of the four lake type groups. No relationship was found between precipitation and nEQR. In rivers, there was no significant relationship between air temperature and nEQR for phytobenthos in any river type. In the Nordic river types, however, nEQR for phytobenthos was significantly related to precipitation, although the direction of response was not clear.

Recent largescale analyses of chlorophyll trends in ~25,000 U.S. lakes (Soranno et al., 2025) and phytoplankton in Scandinavian lakes (Paltsev et al., 2024), highlights the fact that general climate effects can be difficult to identify in large data sets. While finding that climate effects were widespread, Soranno et al. (2025) saw that the effects varied in magnitude and direction. As a result, they could not identify any consistent, generalized relationships between lake chlorophyll and climate variables such as temperature and precipitation. Interestingly, they found that climate signals were most likely to be found in low to moderately impacted lakes where temperature had increased during the study period, while in highly impacted (eutrophied) lakes, the climate signal was masked by the high nutrient inputs from agriculture.

The negative relationship between summer air temperature and phytoplankton nEQR (Fig. 4) was, however, relatively consistent and could represent a true ecological response to temperature. One possible explanation can be that the risk for cyanobacteria blooms increases with higher temperatures (Paerl and Huisman, 2008; Paerl and Huisman, 2009; Pick, 2016; Woolway et al., 2022). Increasing biomass and relative dominance of cyaobacteria, will lead to lower nEQR (see e.g. Phillips et al., 2013), as cyanobacteria typically are indicators of eutrophic conditions. The negative effect of higher temperature on phytoplankton nEQR can also be caused by a shift from oligotrophic taxa having low TP optima, e.g. many chrysophytes that often dominate in spring/early summer in Nordic lakes, to more eutrophic taxa having higher TP optima e.g. large dinoflagellates, chlorophytes and many cyanobacteria that often dominate in summer (TP optima for different species are given in Ptacnik et al., 2009).

The reason why there was no significant effect of temperature on the very shallow, unstratified lakes (L-CB2) can be that the L-CB2 lakes are more impacted by nutrient pollution than the other lake types, thus causing nutrient effects to mask the climate signal, as observed by Soranno et al. (2025). Other factors can also dampen the temperature effect in very shallow lakes, e.g. wind-related resuspension of sediments causing turbid water and thereby light limitation of phytoplankton.

The lack of significant impacts of precipitation on the phytoplankton in lakes can be because precipitation mainly affects nutrient loads (Lucas et al., 2023) and thereby nutrient concentration. This effect is indirectly embedded in the nEQR responses to TP, which was included as a predictor in the statistical models along with the climate variables. Hence, we were in essence estimating climate effects for lakes and rivers with comparable levels of TP, and any significant effects of climate variables in the models should be interpreted as “direct” effects. For temperature, several such direct effects are evident from the literature (e.g. increased risk of cyanobacterial blooms, as discussed above), but there are fewer obvious direct effects of precipitation. Hydrological extremes, which should be captured by the CV value for precipitation used as a predictor in the models, have, however, been found to cause enhanced risk for harmful algal blooms in large, stratified lakes, probably due to increased nutrient load during such events (Sterner et al., 2020). On the other hand, such effects may be opposite in very shallow, unstratified lakes due to flushing and reduced retention time (Richardson et al., 2018). Direct effects of precipitation on nEQR may thus be difficult to detect in large scale data sets like those used above, even though effects could be present locally or in specific lake types.

5.2. *Implications for water management*

Current national boundaries that are clearly higher than the boundaries estimated in this paper (e.g. several of the Polish national boundaries and possibly some of the Finnish national boundaries) are likely to not support good status for phytoplankton in lakes and phytobenthos in rivers. Therefore, taking into account inherent within-type variation among the common intercalibration types, those national nutrient boundaries may need to be adjusted down to at least the upper 95% confidence limit of the estimated boundaries. The tool developed by ECOSTAT (Varbiro et al., 2018) can be used nationally to further explore the relationship between biological and nutrients data. To ensure nutrient boundaries that would be compatible with good status for the phytoplankton in lakes and phytobenthos in rivers, the datasets should include also the lower part of the nutrient gradients where these BQEs are known to be limited by nutrients (e.g. < 100 µg TP/L and < 1 mg TN/L).

Data gaps along the nutrient gradient can be reduced by improved monitoring or by collaborating with neighboring countries, if reference values for nutrients are roughly similar across the countries for the same type of water bodies. The testing with national datasets is important to account for potential biogeographic differences in BQE responses to nutrients.

To close current gaps in boundary setting, such as nutrient targets for Danish rivers and nitrogen boundaries for Swedish rivers and lakes, the estimated boundaries given in this paper can be used as a proxy but should be further tested with refined national datasets and the ECOSTAT toolkit.

6. Conclusions and recommendations to water managers

This paper showed how collaboration across countries, allowing extension of the nutrient gradient within common types of water bodies, enables the derivation of safe nutrient boundaries and thereby supports more harmonised policy implementation in Europe. Such boundaries are fundamental for estimating acceptable nutrient loads and for planning measures to reduce currently excessive loads from different sectors according to source apportionment.

Our results using the binomial logistic regression approach are well in line with results based on linear regressions given in other papers for comparable types of lakes and rivers. Our results showed lower boundaries for lakes than for rivers and lower boundaries for the Nordic region than for the Central-Baltic region. We also confirm that the boundaries increase with alkalinity and humic substances and are lower in stratified than in unstratified lakes.

Some of the current national nutrient GM boundaries are higher than the upper 95% confidence limit of our estimated boundaries, and may not support good status for the BQEs if used as environmental target concentrations. Those boundaries should be validated using national data sets and the ECOSTAT tool kit and potentially be lowered to make sure they support good status for the BQEs.

The space-for-time approach used to assess climate impacts on ecological status of lake phytoplankton indicates negative impacts of higher summer air temperature in stratified lakes, although the effect was small compared to the impact of nutrients. Climate change will continue and become more severe in the coming years. Thus, the quite minor effects of temperature found in this study could become more extensive during the next decades. Cold-water taxa will gradually be substituted with warmer-water taxa and the probability of harmful algal blooms will increase (Woolway et al., 2022). In addition, increasing precipitation and more frequent extreme rain events are predicted to increase nutrient runoff, and contribute to additional deterioration of ecological status unless countermeasures are taken (Jeppesen et al., 2009). Such measures include restoration of riparian areas, reducing tillage, increasing catch-crops and reducing the amount of fertilizer down to crop needs, also taking P-surplus in soils into account (Carpenter, 2005). Using less stringent objectives is also an option in case good status is unachievable after implementing all possible measures. That option will however be a threat to the provision of ecosystem services.

CRediT authorship contribution statement

Jan-Erik Thrane: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Kirstine Thiemer:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Areti Balkoni:** Writing – original draft, Visualization, Formal analysis, Data curation. **Jens Fölster:** Data curation. **Brian Kronvang:** Project administration, Funding acquisition, Data curation, Conceptualization. **Juan Pablo Pacheco:** Data curation. **Jukka Aroviita:** Writing – original draft, Data curation. **Ainis Lagzdins:** Data curation. **Ignacy Kardel:** Data curation. **Geoff Phillips:** Writing – original draft, Supervision, Methodology, Investigation. **Sandra Mingarelli:** Writing – original draft. **Gary Free:** Writing – original draft. **Anne Lyche Solheim:** Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Funding

The work has been supported by the EU Horizon Europe project Project 101060020 —NORDBALT-ECOSAFE (Nitrogen and phosphorus load reduction approach within safe ecological boundaries for the

Nordic-Baltic region, 2022–2025).

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jan-Erik Thrane reports financial support was provided by European Union. Anne Lyche Solheim reports financial support was provided by European Union. Kirstine Thiemer reports financial support was provided by European Union. Jens Fölster reports financial support was provided by European Union. Brian Kronvang reports financial support was provided by European Union. Jukka Aroviita reports financial support was provided by European Union. Ainis Lagzdins reports financial support was provided by European Union. Ignacy Kardel reports financial support was provided by European Union. Areti Balkoni reports financial support was provided by European Union. If there are other authors, they 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

Agnieszka Kolada at the Polish Institute of Environmental Protection is acknowledged for support on Polish classification system for biological quality elements and for providing information on nutrient boundaries for different national types and how they could be linked to the different intercalibration types.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.114685.

Data availability

Data will be made available on request.

References

Atkinson, C.L., Capps, K.A., Rugenski, A.T., Vanni, M.J., 2016. Consumer-driven nutrient dynamics in freshwater ecosystems: from individuals to ecosystems. Biol. Rev. 92 (4), 2003–2023. https://doi.org/10.1111/brv.12318.

Baattrup-Pedersen, A., Johnsen, T.J., Larsen, S.E., Riis, T., 2022. Alkalinity and diatom assemblages in lowland streams: how to separate alkalinity from inorganic phosphorus in ecological assessments? Sci. Total Environ. 823. https://doi.org/10.1016/j.scitotenv.2022.153829.

Barbosa, A.M., Real, R., Munoz, A.R., Brown, J.A., 2013. New measures for assessing model equilibrium and prediction mismatch in species distribution models. Divers. Distrib. 19 (10), 1333–1338. https://doi.org/10.1111/ddi.12100.

Basen, T., Ros, A., Chucholl, C., Oexle, S., Brinker, A., 2022. Who will be where: Climate driven redistribution of fish habitat in southern Germany. PLOS Climate 1 (5), e0000006. https://doi.org/10.1371/journal.pclm.0000006.

Bechmann, M.E., Bøe, F., 2021. Soil tillage and crop growth effects on surface and subsurface runoff, loss of soil, phosphorus and nitrogen in a cold climate. Land 10, 77. https://doi.org/10.3390/land10010077.

Birk, S., Chapman, D., Carvalho, L., Spears, B.M., Estrup Andersen, H., Argillier, C., Auer, S., Baattrup-Pedersen, A., Banin, L., Beklioğlu, M., Bondar-Kunze, E., Borja, A., Branco, P., Bucak, T., Buijse, A.D., Cardoso, A.C., Couture, R.M., Cremona, F., de Zwart, D., Feld, C.K., Ferreira, M.T., Feuchtmayr, H., Gessner, M.O., Gieswein, A., Globevnik, L., Graeber, D., Graf, W., Gutiérrez-Cánovas, C., Hanganu, J., Işkın, U., Järvinen, M., Jeppesen, E., Kotamäki, N., Kuijper, M., Lemm, J.U., Lu, S., Lyche Solheim, A., Mischke, U., Moe, S.J., Nõges, P., Nõges, T., Ormerod, S.J., Panagopoulos, Y., Phillips, G., Posthuma, L., Pouso, S., Prudhomme, C., Rankinen, K., Rasmussen, J.J., Richardson, J., Sagouis, A., Santos, J.M., Schäfer, R. B., Schinegger, R., Schmutz, S., Schneider, S.C., Schülting, L., Segurado, P., Stefanidis, K., Sures, B., Thackeray, S.J., Turunen, J., Uyarra, M.C., Venohr, M., von der Ohe, P.K., Willby, N., Hering, D., 2020. Impacts of multiple stressors on freshwater biota across spatial scales and ecosystems. Nature Ecol Evol. https://doi.org/10.1038/s41559-020-1216-4.

Carpenter, S., 2005. Eutrophication of aquatic ecosystems: Bistability and soil phosphorus. Proceedings Nat. Academy Sci. (PNAS) 102, 10002–10005.

Carvalho, L., McDonald, C., de Hoyos, C., Mischke, U., Phillips, G., Borics, G., Poikane, S., Skjelbred, B., Lyche Solheim, A., Van Wichelen, J., Cardoso, A.C., 2013. Sustaining recreational quality of European lakes: minimizing the health risks from algal blooms through phosphorus control. J. Appl. Ecol. 50, 315–323. https://doi.org/10.1111/1365-2664.12059.

Charles, D.F., Tuccillo, A.P., Belton, T.J., 2019. Use of diatoms for developing nutrient criteria for rivers and streams: A biological condition gradient approach. Ecol. Indicators 96 Part 1, 258–269. https://doi.org/10.1016/j.ecolind.2018.08.048.

Crapart, C., Finstad, A.G., Hessen, D.O., Vogt, R.D., Andersen, T., 2023. Spatial predictors and temporal forecast of total organic carbon levels in boreal lakes. Sci. Total Environ. 870, 2023. https://doi.org/10.1016/j.scitotenv.2023.161676.

Downing, J.A., McCauley, E., 1992. The nitrogen : phosphorus relationship in lakes. Limnol. Oceanogr. 37. https://doi.org/10.4319/lo.1992.37.5.0936.

EC, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy.

EC, 2024. Commission Decision (EU) 2024/721 of 27 February 2024 establishing, pursuant to Directive 2000/60/EC of the European Parliament and of the Council, the values of the Member State monitoring system classifications as a result of the intercalibration exercise and repealing Commission Decision (EU) 2018/229 (notified under document C(2024) 1113). Decision - EU - 2024/721 - EN - EUR-Lex.

Effler, S.E., Schafran, G.C., Driscoll, C.T., 1985. Partitioning light attenuation in an acidic lake. Can. J. Fish. Aquat. Sci. 42, 1707–1711.

[EEA] European Environment Agency, 2019. Urban waste water treatment for 21st century challenges. Briefing no. 5/2019. https://doi.org/10.2800/362039.

[EEA] European Environment Agency, 2024. Europe's state of water 2024: the need for improved water resilience. EEA report 7/2024. Europe's state of water 2024: the need for improved water resilience | Publications | European Environment Agency (EEA).

Free, G., Poikane, S., Lyche Solheim, A., Bussettini, M., Bradley, C., Smith, J., Caroni, R., Bresciani, M., Pinardi, M., Giardino, C., van de Bund, W., 2024. Climate change and ecological assessment in Europe under the WFD – hitting moving targets with shifting baselines? J. Env. Management 370. https://doi.org/10.1016/j.jenvman.2024.122884.

Hall Jr., R.O., Tank, J.L., Dybdahl, M.F., 2003. Exotic snails dominate nitrogen and carbon cycling in a highly productive stream. Front. Ecol. Environ. 1 (8), 407–411. https://doi.org/10.1890/1540-9295(2003)001[0407, ESDNAC]2.0.CO;2.

Heuschele, J., Andersen, T., Walseng, B., Hessen, D.O., 2023. Assessing climatic and spatial variables influencing zooplankton richness for space-for-time predictions. Freshw. Biol. 69. https://doi.org/10.1111/fwb.14193.

Hill, W.R., Griffiths, N.A., 2017. Nitrogen processing by grazers in a headwater stream: riparian connections. Freshw. Biol. 62 (1), 17–29. https://doi.org/10.1111/fwb.12833.

IPCC, 2022. Climate Change 2022: Impacts, adaptation, and vulnerability. contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056 pp., doi:https://doi.org/10.1017/9781009325844.

Järvinen, M., Drakare, S., Free, G., Lyche-Solheim, A., Phillips, G., Skjelbred, B., Mischke, U., Ott, I., Poikane, S., Søndergaard, M., Pasztaleniec, A., Van Wichelen, J., Portielje, R., 2013. Phytoplankton indicator taxa for reference conditions in northern and central European lowland lakes. Hydrobiologia 704, 97–113. https://doi.org/10.1007/s10750-012-1315-6.

Jeppesen, E., Jensen, J.P., Søndergaard, M., et al., 1999. Trophic dynamics in turbid and Clearwater lakes with special emphasis on the role of zooplankton for water clarity. Hydrobiologia 408, 217–231. https://doi.org/10.1023/A:1017071600486.

Jeppesen, E., Kronvang, B., Meerhoff, M., Søndergaard, M., Hansen, K.M., Andersen, H. E., Lauridsen, T.L., Liboriussen, L., Beklioglu, M., Özen, A., Olesen, J.E., 2009. Climate change effects on runoff, catchment phosphorus loading and Lake ecological state, and potential adaptations. J. Environ. Qual. 38, 1930–1941. https://doi.org/10.2134/jeq2008.0113.

Jeppesen, E., Pierson, D., Jennings, E., 2021. Effect of extreme climate events on Lake ecosystems. Water 2021 (13), 282. https://doi.org/10.3390/w13030282.

Jones, R., 1992. The influence of humic substances on lacustrine planktonic food chains. Hydrobiologia 229, 73–91.

Kahlert, M., Fölster, J., Tapolczai, K., 2023. No lukewarm diatom communities—the response of freshwater benthic diatoms to phosphorus in streams as basis for a new phosphorus diatom index (PDISE). Environ. Monit. Assess. 195, 807. https://doi.org/10.1007/s10661-023-11378-4.

Kelly, M., Bennett, C., Coste, M., Delgado, C., Delmas, F., Denys, L., et al., 2009. A comparison of national approaches to setting ecological status boundaries in phytobenthos assessment for the European water framework directive: results of an intercalibration exercise. Hydrobiologia 621, 169–182. https://doi.org/10.1007/s10750-008-9641-4.

Kelly, M., Phillips, G., Teixeira, H., Salas Herrero, M.F., Varbiro, G., Kolada, A., Lyche Solheim, A. and Poikane, S., 2022. Physico-chemical supporting elements in inland waters under the water framework directive: A review of national standards to support good ecological status, EUR 31040 EN, publications Office of the European Union, Luxembourg, 2022, ISBN 978-92-76-51133-5, doi:https://doi.org/10.2760/470539, JRC127875.

Kortelainen, P., 1993. Content of Total organic carbon in Finnish lakes and its relationship to catchment characteristics. Can. J. Fish. Aquat. Sci. 50 (7), 1477–1483. https://doi.org/10.1139/f93-168.

Liu, J.J., Lobb, D.A., Elliott, J.A., Macrae, M.L., Baulch, H.M., Costa, D., 2024. The potential to reduce runoff generation through improving cropping and tillage practices in a sub-humid continental climate. Climate Smart Agriculture 1. https://doi.org/10.1016/j.csag.2024.100021.

Lucas, E., Kennedy, B., Roswall, T., et al., 2023. Climate change effects on phosphorus loss from agricultural land to water: A review. Curr. Pollut. Rep. 9, 623–645. https://doi.org/10.1007/s40726-023-00282-7.

Lyche Solheim, A., Phillips, G., Drakare, S., Free, G., Järvinen, M., Skjelbred, B., Tierney, D., Trodd, W., 2014. Water framework directive intercalibration technical report. Northern Lake phytoplankton ecological assessment methods, 01/2014; report EUR 26503 EN. Publisher: Luxembourg: publications Office of the European Union, editor: Sandra Poikane, ISBN 978-92-79-35455-7. https://doi.org/10.2788/70684.

Lyche Solheim, A., Gundersen, H., Mischke, U., Skjelbred, B., Nejstgaard, J.C., Guislain, A.L.N., Sperfeld, E., Giling, D.P., Haande, S., Ballot, A., Moe, S.J., Stephan, S., Walles, T.J.W., Jechow, A., Minguez, L., Ganzert, L., Hornick, T., Hveem Hansson, T., Stratmann, C.N., Järvinen, M., Drakare, S., Carvalho, L., Grossart, H.P., Gessner, M.O., Berger, S., 2024. Lake browning counteracts cyanobacteria responses to nutrients: evidence from phytoplankton dynamics in large enclosure experiments and comprehensive observational data. Glob. Chang. Biol. 30 (1), e17013. https://doi.org/10.1111/gcb.17013.

Lyche Solheim, A., Thrane, J.E., Mentzel, S., Moe, S.J., 2025. Harmonised biological indicators for rivers and lakes: towards European assessment of temporal trends in ecological quality. Ecol. Indic. 171. https://doi.org/10.1016/j.ecolind.2025.113207.

McKnight, D., Keskitalo, J., Eloranta, P., 2001. Limnology of Humic Waters. In: Journal of Paleolimnology, 25, p. 131. https://doi.org/10.1023/A:1008185628482.

Richardson, J., Miller, C., Maberly, S.C., Taylor, P., Globevnik, L., Hunter, P., Jeppesen, E., Mischke, U., Moe, S.J., Pasztaleniec, A., Søndergaard, M., Carvalho, L., 2018. Effects of multiple stressors on cyanobacteria abundance vary with lake type. Glob. Chang. Biol. 24, 5044–5055. https://doi.org/10.1111/gcb.14396.

Moe, S.J., Mentzel, S., Welch, S.A., Lyche Solheim, A., 2023. From national monitoring to transnational indicators: reporting and processing of aquatic biology data under the European Environment Agency's state of the environment data flow. Front. Environ. Sci. 11. https://doi.org/10.3389/fenvs.2023.1057742.

Paerl, H.W., Huisman, J., 2008. Blooms like it hot. Science 320. https://doi.org/10.1126/science.1155398.

Paerl, H.W., Huisman, J., 2009. Climate change: a catalyst for global expansion of harmful cyanobacterial blooms. Environ. Microbiol. Rep. 1, 27–37. https://doi.org/10.1111/j.1758-2229.2008.00004.x.

Paltsev, A., Bergström, A.-K., Vuorio, K., Creed, I.F., Hessen, D.O., Kortelainen, P., Vuorenmaa, J., de Wit, H.A., Lau, D.C.P., Vrede, T., Isles, P.D.F., Jonsson, A., Geibrink, E., Kahilainen, K.K., Drakare, S., 2024. Phytoplankton biomass in northern lakes reveals a complex response to global change. Sci. Total Environ. 940, 173570. https://doi.org/10.1016/j.scitotenv.2024.173570.

Phillips, G., Pietilainen, O.-P. Carvalho L., Solimini, A., Lyche Solheim, A., Cardoso, A.C., 2008. Chlorophyll–nutrient relationships of different lake types using a large European dataset. Aquat. Ecol. 2008 (42), 213–226. https://doi.org/10.1007/s10452-008-9180-0.

Phillips, G., Lyche Solheim, A., Skjelbred, B., Mischke, U., Drakare, S., Free, G., Järvinen, M., de Hoyos, C., Morabito, G., Poikane, S., Carvalho, L., 2013. A phytoplankton trophic index to assess the status of lakes for the water framework directive. Hydrobiologia 704, 75–95. https://doi.org/10.1007/s10750-012-1390-8.

Phillips, G., Free, G., Karottki, I., Laplace-Treyture, C., Maileht, K., Mischke, U., Ott, I., Pasztaleniec, A., Portielje, R., Søndergaard, M., Trodd, W., Van Wichelen, J., 2014. Water framework directive intercalibration technical report: Central Baltic Lake phytoplankton ecological assessment methods. EUR 26508 EN – Joint Research Centre – Institute for Environment and Sustainability. doi:https://doi.org/10.2788/73991.

Phillips, G., Teixeira, H., Kelly, M.G., Salas Herrero, F., Varbiro, G., Lyche Solheim, A., Kolada, A., Free, G., Poikane, S., 2024. Setting nutrient boundaries to protect aquatic communities: the importance of comparing observed and predicted classifications using measures derived from a confusion matrix. Sci. Total Environ. 912. https://doi.org/10.1016/j.scitotenv.2023.168872.

Picinska-Faltynowicz, J., 2009. Diatom phytobenthos as a tool for assessing the ecological status of polish rivers. Oceanol. Hydrobiol. Stud. 38, 155–161.

Pick, F.R., 2016. Blooming algae: A Canadian perspective on the rise of toxic cyanobacteria. Can. J. Fish. Aquat. Sci. 73, 1149–1158.

Poikane, S., Birk, S., Bohmer, J., Carvalho, L., de Hoyos, C., Gassner, H., Hellsten, S., Kelly, M., Lyche Solheim, A., Olin, M., Pall, K., Phillips, G., Portielje, R., Ritterbusch, D., Sandin, L., Schartau, A.K., Solimini, A.G., van den Berg, M., Wolfram, G., van de Bund, W., 2015. A hitchhiker's guide to European lake ecological assessment and intercalibration. Ecol. Indic. 52, 533–544. https://doi.org/10.1016/j.ecolind.2015.01.005.

Poikane, S., Kelly, M., Cantonati, M., 2016. Benthic algal assessment of ecological status in European lakes and rivers: challenges and opportunities. Sci. Total Environ. 568, 603–613. https://doi.org/10.1016/j.scitotenv.2016.02.027.

Poikane, S., Kelly, M.G., Salas Herrero, F., Pitt, J.A., Jarvie, H.P., Claussen, U., Leujak, W., Lyche Solheim, A., Texeira, H., Phillips, G., 2019. Nutrient criteria for surface waters under the European water framework directive: current state-of-the-art, challenges and future outlook. Sci. Total Environ. 695. https://doi.org/10.1016/j.scitotenv.2019.133888.

Poikane, S., Varbiro, G., Kelly, M.G., Birk, S., Phillips, G., 2021. Estimating river nutrient concentrations consistent with good ecological condition: more stringent nutrient thresholds needed. Ecol. Indic. 121. https://doi.org/10.1016/j.ecolind.2020.107017.

Poikane, S., Kelly, M.G., Várbíró, G., Borics, G., Erős, G., Hellsten, S., Kolada, A., Balázs, A.L., Lyche Solheim, A., Pahissa López, J., Willby, N.J., Wolfram, G., Phillips, G., 2022. Estimating nutrient thresholds for eutrophication management: Novel insights from understudied lake types. Sci. Total Environ. 827, 154242. ISSN 0048-9697. https://doi.org/10.1016/j.scitotenv.2022.154242.

Ptacnik, R., Solimini, A.G., Brettum, P., 2009. 2009. Performance of a new phytoplankton composition metric along a eutrophication gradient in Nordic lakes. Hydrobiologia 633, 75–82. https://doi.org/10.1007/s10750-009-9870-1.

R Core Team, 2024. _R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/>.

Rajczak, J., Schär, C., 2017. Projections of future precipitation extremes over Europe: A multimodel assessment of climate simulations. J. Geophys. Res. Atmos. 122, 10773–10800. https://doi.org/10.1002/2017JD027176.

Scheffer, M., Hosper, S.H., Meijer, M.L., Moss, B., Jeppesen, E., 1993. Alternative equilibria in shallow lakes. Trends Ecol. Evol. 8 (8), 275–279. https://doi.org/10.1016/0169-5347(93)90254-M.

Schindler, D.W., Carpenter, S.R., Chapra, S.C., Hecky, R.E., Orihel, D.M., 2016. Environ. Sci. Technol. 50 (17), 8923–8929. https://doi.org/10.1021/acs.est.6b02204.

Schneider, S., Lindstrøm, E.A., 2011. The periphyton index of trophic status PIT: a new eutrophication metric based on non-diatomaceous benthic algae in Nordic rivers. Hydrobiologia 665, 143–155. https://doi.org/10.1007/s10750-011-0614-7.

Seekell, D.A., Lapierre, J.F., Ask, J., Bergström, A.K., Deininger, A., Rodríguez, P., Karlsson, J., 2015. The influence of dissolved organic carbon on primary production in northern lakes. Limnol. Oceanogr. 60 (4), 1276–1285.

Shatwell, T., Köhler, J., 2019. Decreased nitrogen loading controls summer cyanobacterial blooms without promoting nitrogen-fixing taxa: long-term response of a shallow lake. Limnol. Oceanogr. 64, S166–S178. https://doi.org/10.1002/lno.11002.

Shi, W., Qin, B., Zhang, Q., Paerl, H., Van Dam, B., Jeppesen, E., Zeng, C., 2024. Global lake phytoplankton proliferation intensifies climate warming. Nat. Commun. 15, 10572 (2024). https://doi.org/10.1038/s41467-024-54926-3.

Soranno, P.A., Hanly, P.J., Webster, K.E., Wagner, T., McDonald, A., Shuvo, A., Schliep, E.M., Reinl, K.L., McCullough, I.M., Tan, P., Lottig, N.R., Spence Cheruvelil, K., 2025. Abrupt changes in algal biomass of thousands of US lakes are related to climate and are more likely in low-disturbance watersheds. Proc. Natl. Acad. Sci. USA 122 (9), e2416172122. https://doi.org/10.1073/pnas.2416172122.

Spears, B.M., Chapman, D.S., Carvalho, L., Feld, C.K., Gessner, M.O., Piggott, J.J., Banin, L.F., Gutiérrez-Cánovas, C., Lyche Solheim, A., Richardson, J.A., Schinegger, R., Segurado, P., Thackeray, S.J., Birk, S., 2021. Making waves. Bridging theory and practice towards multiple stressor management in freshwater ecosystems. Water Res. 196. https://doi.org/10.1016/j.watres.2021.116981. ISSN 0043-1354,.

Spinoni, J., Naumann, G., Vogt, J.V., 2017. Pan-European seasonal trends and recent changes of drought frequency and severity. Glob. Planet. Chang. 148, 113–130. https://doi.org/10.1016/j.gloplacha.2016.11.013.

Stagge, J.H., Kingston, D.G., Tallaksen, L.M., et al., 2017. Observed drought indices show increasing divergence across Europe. Sci. Rep. 7, 14045. https://doi.org/10.1038/s41598-017-14283-2.

Sterner, R.W., Reinl, K.L., Lafrancois, B.M., Brovold, S., Miller, T.R., 2020. A first assessment of cyanobacterial blooms in oligotrophic Lake Superior. Limnol. Oceanogr. 65, 2984–2998. https://doi.org/10.1002/lno.11569.

Varbiro, G., Teixeira, H., Kelly, M., Phillips, G., 2018. A Shiny application of a statistical toolkit to assist with the development of nutrient concentrations that would support good ecological status for the Water Framework Directive. In: Phillips, G., Kelly, M., Teixeira, H., Salas Herrero, M.F., Free, G., Leujak, W., Lyche Solheim, A., Varbiro, G., Poikane, S. (Eds.), Best practice for establishing nutrient concentrations to support good ecological status, EUR 29329 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978–92–79–92907-6, JRC112667. https://data.europa.eu/doi/10.2760/55461.

Vuorio, K., Järvinen, M., Kotamäki, N., 2020. Phosphorus thresholds for bloom-forming cyanobacterial taxa in boreal lakes. Hydrobiologia 847, 4389–4400. https://doi.org/10.1007/s10750-019-04161-5.

Wood, S.N., 2006. Low-rank scale-invariant tensor product smooths for generalized additive mixed models. Biometrics 62, 1025–1036. https://doi.org/10.1111/j.1541-0420.2006.00574.x.

Wood, S.N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. J. Royal Statistical Society (B) 73 (1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x.

Woolway, I.R., Sharma, S., Smol, J.P., 2022. Lakes in hot water: the impacts of a changing climate on aquatic ecosystems. Bioscience 72, 1050–1061. https://doi.org/10.1093/biosci/biac052.