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# How efficient are pre-dams as reservoir guardians? A long-term study on nutrient retention

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ABSTRACT

Assessing nutrient loading and processing is crucial for water quality management in lakes and reservoirs. Quantifying and reducing external nutrient inputs in these systems remains a significant challenge. The difficulty arises from low monitoring frequencies of the highly dynamic external inputs and the limited availability of measures to reduce diffuse source loading. One option for the latter is the use of pre-dams, i.e. small impoundments at the inflow points into reservoirs, designed to retain nutrients by algal uptake and sedimentation. This study analyzes long-term (ranging from 8 to 22 years) nutrient and discharge time series for nine German pre-dams to assess their retention capacity. For that, we (i) quantified nutrient loading using four different mathematical methods, (ii) derived their retention efficiencies, and (iii) identified environmental factors determining the retention of nitrogen (N), phosphorus (P), and silica (Si). We show that retention of soluble reactive phosphorus (SRP) (43.6 %) and total phosphorus (TP) (39.9 %) is far higher than for nitrate ($NO_3$) (15.3 %) and Si (15.9 %). The retention efficiency for SRP and TP was higher during the warm seasons because of higher algal nutrient uptake and thus higher nutrient sedimentation. Mixed effects models documented a significant positive effect of the pre-dams' hydraulic residence time (HRT) on retention efficiency. Pre-dams provide substantial service in retaining nutrients and help to protect downstream waterbodies from nutrient inputs. They provide effective measures for trapping nutrients including those originating from non-point sources.

## 1. Introduction

Excessive nutrient enrichment in water can cause toxic algal blooms and thus be dangerous for humans and ecosystems and impair the quality of water intended for drinking (EEA, 2018). Therefore, water quality management of lakes and reservoirs requires a sound assessment of nutrient loading and processing. In recent years, progress has been reached in reducing nutrient concentrations in lakes (e.g. Frenken et al., 2023; Jeppesen et al., 2005), particularly with respect to lowering external point sources or internal loading (e.g. Huser et al., 2016a,b). To control point sources, proper wastewater management is a key instrument (Tong et al., 2020). However, the control and assessment of external loading from non-point sources, e.g. agriculture, remains a major challenge (Carvalho et al., 2019; EEA, 2018). Firstly, concentration and discharge are extremely dynamic and measurements are usually not available in the needed spatial and temporal resolution. Secondly, the reduction of the external loading is notoriously difficult as agricultural practices still rely on strong fertilizer use. Their long-term practice leads to lasting effects making agriculture the major driver of non-point nutrient loading at continental scales (EEA, 2018). Additionally, different approaches deliver different results (Luo et al., 2023; Xue et al., 2022).

The operation of pre-dams, i.e. small impoundments at the inflow points into reservoirs, designed to retain nutrients by algal uptake and sedimentation, is one of the few instruments to reduce external nutrient load. They retain nutrients that have already entered the river network irrespective of their source. Pre-dams typically have HRT of a few days or weeks, and have a surface overflow in order to maximize trapping of

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**Table 1**
Pre-dams' main morphological and time series characteristics.

| Reservoir | Pre-dam | Abreviation | Volume ($10^6$ $m^3$) | Surface area ($km^2$) | Max (mean) depth (m) | Catchment area ($km^2$) | Mean HRT (d) | Time series | Nutrient Sampling | Si data | Reservoir authority |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Droeda | Ramoldsreuth | DPD1 | 0.136 | 0.0511 | 6.2 (2.6) | 27.8 | 9 | 1998–2020 (22 years) | Monthly | Yes | Landestalsperrenverwaltung Sachsen (LTV) |
| | Bobenneukirchen | DPD2 | 0.194 | 0.0563 | 6.3 (3.4) | 15.1 | 28 | | Monthly | Yes | |
| Rappbode | Rappbode | RPD1 | 1.25 | 0.218 | 17 (5.3) | 48.1 | 29 | 2012–19 (7 years) | Biweekly | Yes | Talsperrenbetrieb Sachsen-Anhalt |
| | Hassel | RPD2 | 1.45 | 0.288 | 14 (5) | 44.5 | 53 | | Biweekly | Yes | |
| Poehl | Neuensalz | PPD1 | 0.21 | 0.056 | 9.5 (3.7) | 21.8 | 21 | 2008–21 (13 years) | Monthly | No | LTV |
| | Thossfell | PPD2 | 1.23 | 0.33 | 11 (3.7) | 109.1 | 19 | | Monthly | No | |
| Grosse Dhuenn | Grosse Dhuenn | GDPD1 | 7.5 | 0.67 | 28.4 (11.2) | 59 | 84 | 2004–17 (13 years) | Biweekly | No | Wupperverband |
| | Kleine Dhuenn | GDPD2 | 0.4 | 0.106 | 12.9 (3.8) | 14 | 14 | | Biweekly | No | |
| Bautzen | Oehna | BPD1 | 0.518 | 0.163 | 6 (3.1) | 293 | 2 | 2007–18 (11 years) | Biweekly | Yes | LTV |

sedimenting material (Fig. S2). They also facilitate nutrient retention by algal uptake and sedimentation (Paul, 2003) and have a history of implementation in drinking water reservoirs (Benndorf and Pütz, 1987). Pre-dams retain nutrients in a similar way to chains or cascades of lakes or reservoirs (Soares and Calijuri, 2022). The determination of the nutrient loads entering and leaving the pre-dam is the basis for the retention efficiency assessment. However, the different procedures for calculating the load can deliver heterogeneous results. Quantifications are furthermore often impaired due to the low, e.g. monthly, temporal resolution of nutrient monitoring. Besides that, there is a lack of comparative long-term analyses so the influence of environmental drivers and reservoir-specific properties cannot be assessed.

Our study tackles these issues and follows a three-step workflow with the specific research tasks: (i) quantify nutrient fluxes/loading by using and comparing different mathematical approaches for the three key algal macronutrients N, P, and, Si, (ii) calculate retention efficiencies for nine German pre-dams based on long-term data, and (iii) statistically analyze the major factors determining the retention efficiencies for N, P and Si and potential seasonal differences in retention.

According to Benndorf and Pütz (1987), we expect phytoplankton nutrient uptake and subsequent sedimentation to be the primary factor influencing retention in pre-dams, which may be lower during winter due to low light intensity and temperature (Pütz and Benndorf, 1998). We also hypothesize that SRP, TP, $NO_3$, and Si elimination in pre-dams correlate with the hydraulic retention time (HRT) (Paul, 2003).

Our methodology involves four methods (two linear and two non-linear) for load estimation, which differ in complexity, aiming to determine whether there are systematic differences among them. These specific methods were chosen because they are commonly used by stakeholders and in literature to calculate nutrient loads. The linear methods are based on algebraic formulations whereas the non-linear methods are data-driven and include a statistical component. We also quantify differences in retention efficiency among the studied nutrients and pre-dams to identify driving environmental factors and site-specific characteristics that affect retention efficiency.

The novelty of this study includes (i) a fully quantitative assessment of nutrient retention including the comparison of four load calculation methods in several reservoir systems and over long time series; (ii) a separate analysis for the three major nutrients N, P, and Si; (iii) evaluation of the variability of retention efficiency at interannual and seasonal time scales, and; (iv) a statistical analysis of the drivers in nutrient retention using Linear Mixed Models (LME).

## 2. Methods

### 2.1. Study sites

The study was conducted in nine pre-dams from five German reservoir systems (Fig. S1). These pre-dams cover a wide range (i.e. more than one order of magnitude) of morphometric and hydrological characteristics (Table 1) and hence represent a typical sample of these engineered infrastructures (Fig. S2). Detailed information about the reservoirs can be found in the Supplementary Material.

### 2.2. Monitoring data

The data includes biweekly or monthly measurements of nutrient concentration [mg $l^{-1}$] (Table 1) and daily discharge [$m^3$ $d^{-1}$] for nine pre-dams. The nutrients analyzed were SRP, TP, $NO_3$, and Si. The data was provided by the responsible German reservoir authorities (Landestalsperrenverwaltung Sachsen, Talsperrenbetrieb Sachsen-Anhalt, and Wupperverband). This included two data sets per pre-dam at different temporal resolutions: (i) daily discharges of inflows (or outflows alternatively) and (ii) nutrient concentrations at the specific sampling dates (at monthly or biweekly scale). All data were quality-checked, merged into one consistent data structure, and processed for load estimation and retention efficiency calculations. Information on the standard methods used for chemical analyses is provided in the supplementary material.

#### 2.2.1. Assumptions

The data analysis was based on the following assumptions:

I. Inflow discharge was considered equal to outflow discharge for all the pre-dams, considering that the pre-dams operate in continuous overflow, short HRT, and negligible evaporation losses.
II. Retention efficiency is calculated by load estimates of inflows and outflows of the pre-dam (see below).

#### 2.2.2. Calculated derived and explanatory variables

The HRT ($\tau$, days) was calculated as the ratio of the pre-dam volume (V, $m^3$) to the discharge (Q, $m^3 \cdot s^{-1}$) according to Equation 1.

$$\tau = \frac{V}{Q} \times 3600 \times 24 \text{ (days)} \tag{1}$$

The areal load ($L_a$, tonne $km^{-2}$ $year^{-1}$) was calculated by the ratio of the annual inflow load ($L_{in}$, tonne $year^{-1}$) to surface area ($A$, $km^2$, see Equation 2).

$$L_a = \frac{L_{in}}{A} \ \left(tonne \times km^{-2} \times year^{-1}\right) \quad (2)$$

### 2.3. Load estimation

The nutrient load can be calculated by multiplying discharge and concentration. However, load estimation from hydrological observations is challenged by the fact that discharges are usually measured continuously (hourly or at least daily) while concentration measurements take place at a far coarser temporal resolution (usually monthly or biweekly). We quantified the yearly nutrient load by using four mathematical approaches: (i) unweighted (UA) and (ii) weighted averaging of concentration and discharge (WA), (iii) statistical concentration dynamics predictions based on GAMs (Generalized Additive Models), and (iv) the R package EGRET (Exploration and Graphics for River Trends) developed by the USGS (Hirsch and De Cicco, 2015). The first two methods are based on algebraic formulations and the latter two are data-driven statistical approaches.

a) UA: Unweighted averaging method ("Standard method" in Hilden (2003))

This linear method determines the load L (tonne·year$^{-1}$) based on the number of available samples (N) by multiplying the measured nutrient concentrations (c, mg l$^{-1}$) by the corresponding daily average discharges (Q, m$^3$ s$^{-1}$) at each day of sample i resulting in an estimate of loading rate given as mass per time. These loading rates are simply averaged and then converted to a unit of tonne per year. The annual load is estimated by Eq. (3) and represents a simple (unweighted) averaging of loading rates over all available samples in a given year.

$$L_{UA} = \frac{365 \times 86400}{1000 \times 1000} \frac{1}{N} \sum_{i=1}^{N} c(t_i) \times Q(t_i) \quad \left(tonne \times year^{-1}\right) \quad (3)$$

b) WA: Weighted averaging method ("Discharge-corrected standard method" in Hilden (2003))

This method is a refinement of WA by accounting for potential sampling bias, which is likely to occur when water quality sampling is at a much lower frequency (usually biweekly or monthly) than discharge gauging (usually daily or hourly). In such a sampling design, the representativeness of rare events (samples during high or low discharge) may bias the annual load and may result in over- or underestimations. Therefore, in WA the annual load from Method UA ($L_{UA}$) is weighted by the ratio of annual mean discharge $Q_m$ (average of the daily discharges $Q_i$ of the given year) to the mean sampled discharge $Q_s$ (i.e. mean of discharges $Q_{s,j}$ during sampling days j when both nutrient concentration and discharge were sampled, Eq. 4).

$$L_{WA} = L_{UA} \frac{\frac{1}{365}\sum_{i=1}^{365} Q_i}{\frac{1}{N}\sum_{j=1}^{N} Q_{s,j}} \quad \left(tonne \times year^{-1}\right) \quad (4)$$

These two linear methods UA and WA were chosen because they are commonly used by stakeholders and in literature to estimate nutrient load in pre-dams (Paul, 1995). Also because they are defined as standard methods in practical recommendation sheets (Hilden, 2003).

c) Generalized Additive Models (GAM)

This method is based on a statistical time series model with non-linear smoothing terms for the long-term trend, seasonal dynamics, and a runoff-dependent component using generalized additive models (GAM), see Wood (2011). GAM method fits the data with local splines, smoothing over the data in order to catch the inherent data variability patterns. GAMs do not have a single fixed formula but a flexible modeling framework that can incorporate a variety of functions.

In order to define the GAM model we used the "gam()" function from the "mgcv" R package (Wood, 2011) with concentration as the response variable and smoothing splines of year, day of the year, and discharge as predictors. The resulting GAM model was then used to predict daily concentration values based on the provided daily discharge data. The daily nutrient load is then calculated by multiplying the predicted concentration by the daily discharge. Daily nutrient loads were summed over the whole year in order to achieve yearly estimates. Note, that we used a circular spline term for the seasonal predictor (day of the year).

d) EGRET: Exploration and Graphics for River Trends

The EGRET method (USGS, R package EGRET) is also a statistical-based approach that describes dynamics in water quality and hydrology data and is a recommended procedure by the US Geological Survey (USGS). EGRET is similar to GAM as it is based on a flexible, data-driven statistical approach. It uses a Weighted Regression on Time, Discharge, and Season (WRTDS) to describe long-term dynamics for the various water-quality components as nutrient concentrations or any other solutes (Hirsch and De Cicco, 2015). The daily and subsequent annual loads were calculated using the regular function "modelEstimation()" of the "EGRET" R package as defined in the documentation (Hirsch and De Cicco, 2015). This involves a similar procedure as in GAM since the EGRET model first computes daily concentration values based on daily discharge, which are then converted to loads by multiplication of concentration and discharge at a daily scale. This method was also used in this study to calculate monthly retention efficiency based on these daily mode outputs.

### 2.4. Retention efficiency calculation

Based on the estimates of the yearly inflow load ($L_{in}$) and outflow load ($L_{out}$), we calculated nutrient retention efficiencies (R) according to Eq. (5):

$$R[\%] = \frac{L_{in} - L_{out}}{L_{in}} * 100 \quad (5)$$

Both load and yearly retention efficiency calculations were carried out for SRP, TP, $NO_3$, and Si for nine pre-dams.

### 2.5. Statistical analysis

We statistically analyzed the calculated retention efficiencies (response variable) across all pre-dams and years using different explanatory variables. Since yearly-based retention efficiencies were pseudo-replicated within each pre-dam, we selected Linear Mixed Effect Models (LME) for data analysis (Bates et al., 2015). In order to account for the pseudo replication within pre-dams over the multiple years for each pre-dam and the four methods, we defined pre-dams, years, and methods as random effects with the latter two nested within pre-dams. The type of nutrient (N, P, Si) as well as various other environmental variables (retention time) were evaluated as fixed effects. We applied model selection over competing models and removed model components with non-significant p-values.

We approximated the coefficient of variation $R^2$ by using the method of Stoffel et al. (2021) specifically designed for LMEs. Finally, we approximated the relative importance of each environmental variable by recalculating the LME based on z-scores calculated from normalized data (i.e. transforming the mean of zero and a standard deviation of 1) using the R function scale(). In this procedure, the different scales in the various variables (e.g. residence time, radiation, depth) were unified to produce dimensionless numbers. In an LME with z-score variables, the model estimates (i.e. the slopes) are a measure of their relative effect size and can be interpreted as relative importance.

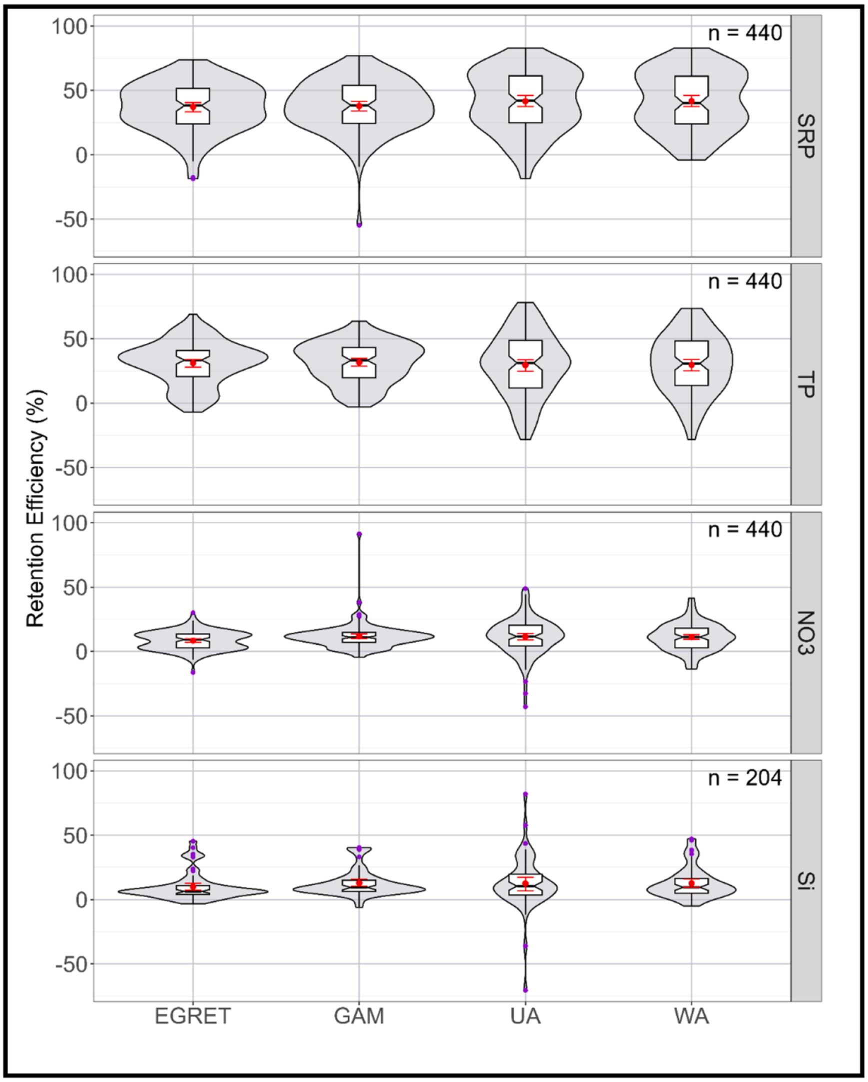


**Fig. 1.** Retention efficiency (%, y-axis) for each load calculation method (x-axis) EGRET, GAM, UA, WA) for each nutrient (horizontal panels, SRP, TP, $NO_3$, Si). Violin plots show probability density distribution, boxplots median, and Q25-Q75 range, means are shown in red dots, and outliers in purple dots. The 95 % confidence interval error bars of the means are shown in red. The 95 % confidence intervals of the medians are displayed as a notch around the boxplot median.

### *2.6. Code transparency and open access availability by package creation*

An all-inclusive R function was developed using the R programming language to compile the estimation of load and retention efficiency using the methods described above. This new R function "ret_eff()" was added to the Seefo R package. It is publicly available in the GitHub environment under https://github.com/shatwell/seefo.

All analyses, model calculations, and plots were made with R version 4.1.3 (R Core Team, 2021). The following R packages were used: "mgcv" for GAMs (Wood, 2011), "lme4" (Bates et al., 2015) for LME, "partR2" for partition variance analysis (Stoffel et al., 2021), "EGRET" (Hirsch and De Cicco, 2015) for calculating nutrient load, "DHARMa" (Hartig, 2022) and "ggeffects" (Lüdecke, 2018) to check for residual diagnostics. Additionally, ArcGis Pro (Esri, 2024) was used to create Fig. S1.

## 3. Results

### *3.1. Comparison of the different calculation methods for retention efficiency*

All four methods to calculate retention efficiency showed similar results with respect to mean or median retention values for all nutrients. However, the UA method generated more outliers and had a wider variability when compared to the other methods (Fig. 1). Along with this agreement in the overall medians, the calculated retention efficiencies varied depending on the specific pre-dam and year. However, the variability contribution from the four methods remained rather small (0.8 %), as shown by an LME model (Table 2), indicating that the methods of calculation are not strongly influential. The pre-dams contributed 14 %, and the interannual variability accounted for 8 %, with the remaining 76 % as residual variability. In other words, the variance partitioning showed that variability is highest among pre-dams, followed by year-to-year variation. The different methods remained unimportant compared to the other random factors. In the few cases where the four methods deviated from each other for a given pre-dam, year, and nutrient, the UA method was responsible while the other methods were more consistent among each other (Fig. 1). Given this agreement among the four methods, we aggregated retention efficiencies by taking the average over all 4 methods in the further statistical analysis for each pre-dam and year (see Supplement for further details on method comparisons, Fig. S3).

Regarding the fixed factors, the LME-model confirmed that retention efficiencies were significantly different (Table 2) between nutrients and also that the effect of HRT was significant. Note that, since

**Table 2**
Results from an LME model of yearly nutrient retention efficiencies in the nine pre-dams. The type of nutrient and HTR were selected as fixed effects as they showed significant influence while other fixed factors evaluated remained insignificant. Note that HRT was log-transformed (natural log). Due to pseudoreplication within pre-dams along with years and calculation method, we chose pre-dam as well as method and year, nested in pre-dam, as random factors. The stars indicate statistical significance with: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. The partition of the variance analysis showed that the total explanatory power of the full model, given as approximated R2, is substantial (conditional R2 = 0.50) and even the fixed factors alone explain about one-third of the variability (marginal R2) is 0.34. The complete model result is displayed in Fig. S.6.

| Random effects | Variance | | | | |
|---|---|---|---|---|---|
| Pre.dam:year | 24.35 | | | | |
| Pre.dam: method | 2.30 | | | | |
| Pre.dam | 42.59 | | | | |
| Residual | 219.80 | | | | |
| Fixed effects | Estimate | Standard Error | df | t-value | p-value |
| Intercept | −1.98 | 4.95 | 30.01 | −0.400 | 0.69 |
| Si | 8.43 | 1.16 | 1621.13 | 7.222 | 7.86e-13*** |
| SRP | 28.91 | 0.94 | 1611.56 | 30.709 | <2e-16*** |
| TP | 18.85 | 0.94 | 1611.56 | 20.025 | <2e-16*** |
| HRT (log) | 4.57 | 1.49 | 45.52 | 3.060 | 0.004** |

**Table 3**
Results of the LME model using monthly retention efficiency for each pre-dam and year (after applying z-scores). Note that we used the ratio of inflow load and inflow discharge, i.e. the mean inflow concentration, instead of including them separately simply because they showed a high covariation. The explanatory power given as approximated R2 was at 0.57 for the full model (conditional R2) and 0.46 for the fixed effects alone (marginal R2). The sample size (n) was 5187. For significance levels, see Table 2. The Fig. S.7 displays the complete model result.

| Random effects | Variance | Standard deviation | | | |
|---|---|---|---|---|---|
| Pre.dam:year | 0.022 | 0.149 | | | |
| Pre.dam | 0.082 | 0.292 | | | |
| Residual | 0.363 | 0.602 | | | |
| Fixed effects | Estimate | Standard Error | df | t-value | p-value |
| Intercept ($NO_3$) | −0.59 | 0.106 | 8.33 | −5.61 | 0.000435*** |
| Si | 0.02 | 0.039 | 5072.69 | 0.67 | 0.499641 |
| SRP | 1.34 | 0.031 | 5071.92 | 42.14 | <2*e-16*** |
| TP | 0.87 | 0.031 | 5071.06 | 27.83 | <2*e-16*** |
| HRT (log) | 0.73 | 0.022 | 4557.33 | 32.30 | <2*e-16*** |
| Mean depth | −0.27 | 0.100 | 8.30 | −2.72 | 0.024991* |
| Solar radiation | 0.18 | 0.010 | 4989.62 | 16.75 | <2*e-16*** |
| Weighted concentration | 0.15 | 0.020 | 5072.90 | 7.74 | 1.12e-14*** |

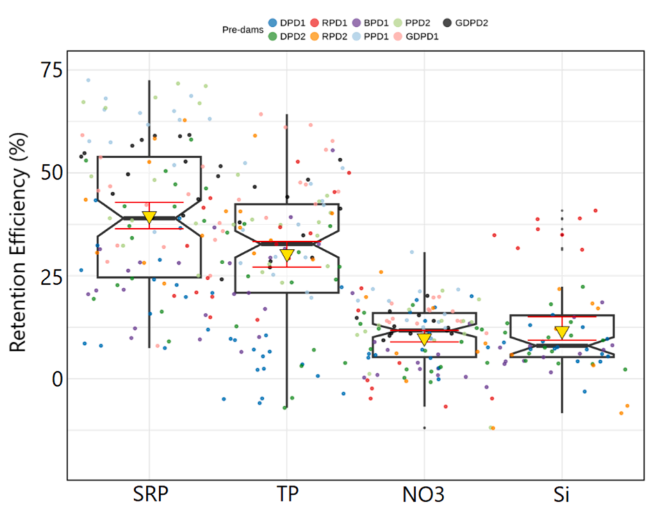


**Fig. 2.** Boxplots for yearly retention efficiency for SRP, TP, $NO_3$, and Si in nine pre-dams (averages of all four methods). The colors represent the different pre-dams (legend on the top, abbreviations see Table 1). The yellow triangle in each boxplot represents the arithmetic mean over all years and pre-dams while the horizontal black line in the boxes shows the median. The sample size (n) for nutrients and pre-dams are SRP (124), TP (124), $NO_3$ (124), and Si (70), DPD1–2 (84), RPD1–2 (32), BPD1 (48), PPD1–2 (42), GDPD1–2 (39). Note that values within each nutrient were plotted with horizontal scatter.

sedimentation follows first-order kinetics, mean HRT was log-transformed and an increase in HRT by one unit (log-transformed days) was associated with an average increase of 4.57 % in retention efficiency.

### 3.2. Nutrient-specific retention efficiencies and variability over pre-dams and years

Retention efficiencies differed significantly between nutrients (Fig. S7). Observed mean retention efficiencies for the phosphorus components, SRP (43.6 %) and TP (39.9 %), were higher than for $NO_3$ (15.3 %) and Si (15.9 %) (Fig. 2). There were also systematic differences

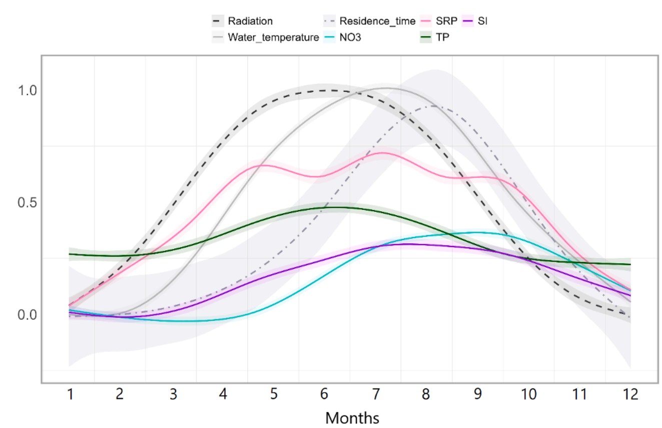


**Fig. 3.** Seasonally scaled dynamics of solar radiation (kWH $m^{-2}$ $month^{-1}$), water temperature (°C), residence time (HRT in days), and retention efficiency for SRP, TP, $NO_3$, and Si aggregated over all pre-dams. To enhance comparability, the variables were scaled by dividing by the maximum value, i.e. all variables scale within the interval [0, 1]. Smoothed curves were fitted using a circular (yearly scale) Generalized Additive Model (GAM) showing predictions (lines) and confidence intervals (shaded areas).

among the pre-dams (Figure S9), the retention efficiency for some pre-dams and years, respectively even turned out as negative values in the case of TP (5.45 % below zero), $NO_3$ (10 % below zero), and Si (5.17 % below zero), meaning that a net mobilization of these nutrients took place in specific years and pre-dams. The variability contribution from the pre-dams (14.7 % of random variability) was almost twice as high as the interannual variability (8.4 % of random variability) pointing to systematically different performances of the studied pre-dams (LME, see Table 2).

### 3.3. Variability and covariation of nutrient retention at monthly vs. yearly scales

High SRP and TP retention efficiency coincided with months of high radiation and water temperature pointing to the decisive role of phosphorus uptake by phytoplankton. However, the seasonal course of the retention efficiency for SRP was broader than that of TP. Interestingly,

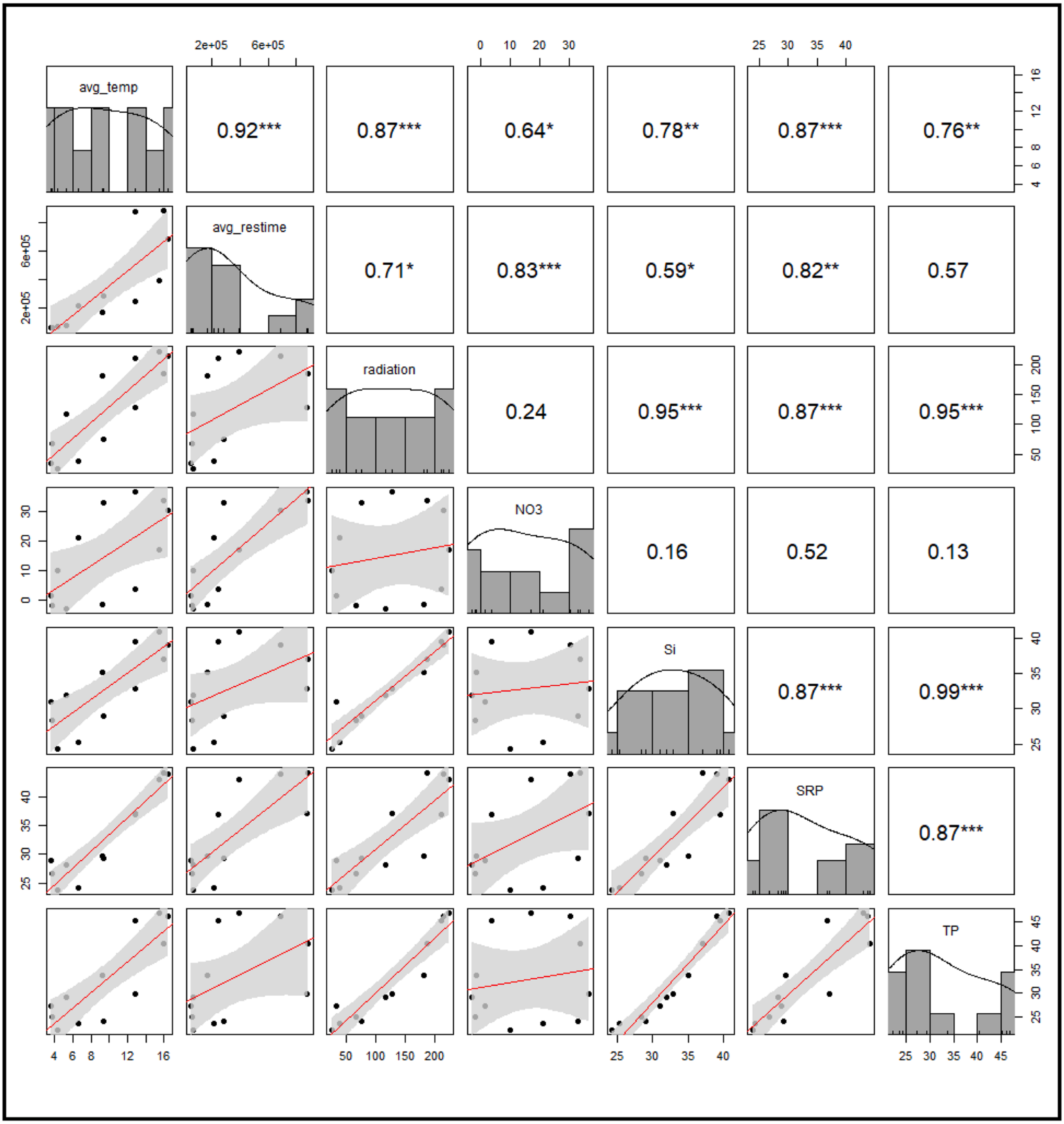


**Fig. 4.** Correlation plot using Spearman's rank correlation coefficient for monthly mean retention efficiency for four nutrients (SRP, TP, $NO_3$, and Si), HRT (avg_restime), water temperature (avg_temp), and solar radiation. The stars indicate statistical significance with: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. The diagonal displays histogram plots for the corresponding variable. The red line is a regression line and the grey shaded area is the 95 % confidence interval.

for $NO_3$ the retention efficiency peaked a little later in the year and hence did not coincide with the months of elevated radiation and scaled best with HRT. The seasonality of the retention efficiency for Si peaked in late summer, between those of TP and $NO_3$, respectively.

A Spearman correlation analysis using monthly averaged values from the whole dataset (Fig. 4) demonstrated that these statements were statistically significant and the single best predictor for nutrient retention was radiation (SRP, TP, Si), HRT ($NO_3$), and water temperature (Si). There was also a positive correlation between the monthly retention efficiency of SRP and TP ($r = 0.87$, $p < 0.001$, Fig. 4). Besides that, the correlation between both TP and SRP with Si monthly retention efficiency was also strong and positive ($r = 0.99$*** and $r = 0.87$***).

### 3.4. LME model for monthly retention efficiency

The monthly derived retention efficiencies in each pre-dam and year were finally evaluated in a full LME model including hydrological, morphological, and climatological variables. This allowed us to account for intra- and interannual variability in the predictors and the pseudoreplication within each pre-dam in one coherent statistical model. The model estimates for the fixed factors explained 46 % of the variability and confirmed that phosphorus is retained more efficiently than Si and $NO_3$. HRT, radiation (Table 3), inflow concentration, and mean depth were significant drivers indicating that meteorological, hydrological, and morphological characteristics influence retention. Among the random factors, variability within pre-dams explained 18 % of random variability while interannual variability contributed only 5 %. We identified HRT as the most influential variable followed by mean depth and radiation (Table 3, see methods for calculation of relative importance).

## 4. Discussion

### 4.1. Are there systematic differences among the chosen methods?

It is known in the literature that the Unweighted Average (UA) method (Eq. (3)) can lead to systematic deviations due to the unprecise representation of flood events (Quilbé et al., 2006; Treunert et al., 1974; Valerio et al., 2022; Williams et al., 2015). For TP load, the errors could range from 10 % to 14 % (Valerio et al., 2022). Nevertheless, it is a simple approach still used by recent papers (Audet et al., 2020; Barbosa et al., 2019; Kumwimba et al., 2022) and in governmental procedures. In this study, the results of the UA method had the largest number of outliers when compared to the other three methods (Fig. 1). In the rare cases where the values from the four methods deviated to some extent, the UA method was usually the cause (Fig. 1) while the other three methods showed higher consistency. Aside from this higher, partly erratic, variability, the UA method still captured the average retention efficiency satisfactorily as long as a reasonable number of years were included. Therefore, the ensembled mean of all four methods was used, providing a reasonable and robust load estimate.

### 4.2. Which nutrient is retained best in pre-dams?

Regarding the phosphorus fractions, for six (DPD1–2, GDPD2, RPD2, PPD1–2) out of nine pre-dams, the mean SRP retention was higher than TP agreeing with literature for German pre-dams (Determann et al., 2024; Paul, 2003; Pütz and Benndorf, 1998). Three (BPD1, GDPD1, and RPD1) out of nine studied pre-dams presented higher mean TP retention when compared with SRP (Table 1 and Fig. 1) agreeing with findings in literature for Chinese and Luxembourgian pre-dams (Kumwimba et al., 2022; Salvia-Castellvi et al., 2001).

The different retention efficiency for SRP and TP is mainly explained by the HRT which needs to be long enough to allow the development of fast-settling phytoplankton species (such as diatoms) but short enough to prevent dominance of algae with low settling rates (such as cyanobacteria) (Hülsmann et al., 2021; Pütz and Benndorf, 1998). In instances where SRP is retained effectively but TP is not, phytoplankters have obviously taken up SRP, yet the sedimentation was insufficient (main mechanism for TP removal). This may be either because of too low HRT or because of the motility or buoyancy of the dominating phytoplankton species (e.g. flagellates, cyanobacteria). Previous results from RPD1–2 (Friese et al., 2014) support this interpretation: RPD1 was dominated by diatoms in summer and showed (1) better TP retention than SRP and (2) the highest Si retention. In contrast, RPD2 was dominated by cyanobacteria and showed higher SRP retention compared to TP and a reduced Si retention (See Fig. S.11–14).

Biological structures in pre-dams can also play a role in P and N retention, e.g. by extending the contact of water with water plants and therefore reinforcing nutrient uptake and sedimentation (Cui et al., 2022; Nikolakopoulou et al., 2020; Wiatkowski, 2011). Considering that pre-dams are relatively shallow (Table 1) submerged macrophytes can shape local nutrient retention with potential network-wide cascading effects of improved water quality contributing to net particulate P retention and net dissolved P release (Carpenter and Lodge, 1986; van Wijk et al., 2022).

The higher P retention relative to $NO_3$ in Fig. 1 agrees with findings for lakes and reservoirs globally (Wu et al., 2022). But Wiatkowski (2011) found higher $NO_3$ (69 %) retention compared to SRP (33 %) in a Polish pre-dam (HRT = 12 days) indicating that in some special cases, nitrogen removal can be high, e.g. when denitrification is intense. Wendt-Potthoff et al. (2014) found higher denitrification activity in RPD2 compared to RPD1 due to the higher nutrient input from the catchment, including increased $NO_3$, and the resulting higher trophic state. However, denitrification usually operates at lower rates in pre-dams due to their short HRT and weak stratification (Paul, 2003). Also, typical suspended particles in lakes and inflows show higher adsorptive capacities for phosphate compared to $NO_3$. Therefore, pre-dams are often not excessive nitrogen sinks over annual timescales (Kong et al., 2019; Whitney et al., 2023).

At the global scale, Si retention in standing waters plays a significant role in the land-to-ocean transport of Si (Harrison et al., 2012; Maavara et al., 2014). Also, Si controls phytoplankton growth, but only for diatoms (Friese et al., 2014; Kudela and Dugdale, 2000; Parekh and Mccully, 2004; Wang et al., 2010; Wentzky et al., 2018) which are often dominating in pre-dams (Friese et al., 2014). Interestingly, not many studies analyzed Si retention efficiency in pre-dams. Our results had a similar Si annual mean retention efficiency (15.9 %) as the few findings in the literature (15.3 % Paul, 2003).

In a few years, net mobilization of TP, $NO_3$, and Si took place and the outflow load was higher than the inflow load. Some factors might have driven the negative retention efficiency for TP, $NO_3$, and Si like internal sediment release and mineralization. For $NO_3$, high mineralization rates of allochthonous detritus (Morling et al., 2017), low denitrification rates, and atmospheric deposition (Kong et al., 2019; Paul, 2003) can mediate net release. The SRP retention was never negative indicating that phosphate uptake by algae was sufficiently high in all pre-dams and years.

In general, algal uptake is a key process that shapes nutrient retention. Phosphate uptake has a special role here as it mediates SRP retention but not necessarily TP retention. For instance, if an algal population takes up all SRP, it is still in the system as intracellular, particulate phosphorus and therefore still included in the TP pool. When then a flood event flushes the population out of the pre-dam, realized TP-retention is zero, or even negative if sediment release is sufficiently high.

### 4.3. Which pre-dams performed better (or worse) and why?

Some pre-dams retained more nutrients than others. Variation in HRT alone cannot explain these differences as the correlation with the HRT was moderately low (Fig. 2) although not so distant from literature findings for TP in lakes ($r^2 = 0.19$ for this study vs. $r^2 = 0.35$ by Brett and Benjamin (2008)). Considering the average retention efficiency, BPD1 and DPD1 showed lower retention efficiencies. GDPD1 (HRT = 84 days) had the highest TP retention, and PPD1 (HRT = 21 days) had the highest SRP and $NO_3$ retention efficiency (Fig. S.8). We believe that besides HRT, other internal factors come into play, namely the sedimentation characteristics of the dominating algae and the nutrient release of the sediments. For example, some pre-dams were subjected to partial sediment removal, and others were not, which may explain the difference in behavior. This intervention could cause an increase in the HRT since there is more volume available and nutrient-rich sediments, potentially acting as an internal nutrient source, are removed from the system. At the same time, depending on how the sediment removal is performed, it can also cause a nutrient resuspension from the sediment into the water column during the dredging. A close analysis of the above-mentioned processes requires more detailed studies derived from high-frequency nutrient monitoring so that the impact of short-term dynamics (e.g. flash floods) can be resolved. In that respect, the concept of average HRT is maybe too simple and the discharge dynamics at short time scales, particularly floods, have a strong influence besides even more complex factors such as stratification and interflow processes (Pilotti et al., 2014). The retention efficiency in pre-dams can also be altered by nutrient concentration variability through hydrological events and stratification that creates a layer with shorter HRT (Determann et al., 2024).

### 4.4. Drivers of retention efficiency at monthly vs. yearly scales load

The correlations for retention efficiency among nutrients and with environmental drivers showed higher coefficients of determination at the monthly scale than for the yearly scale (Fig. S5 and Fig. S6). As a matter of fact, intra-annual nutrient retention efficiency variability was higher than interannual variability. This is mainly due to the strong seasonality in temperate zones where the air and water temperature, light availability, and often also HRT vary considerably among the seasons (Fig. 3). Adding to that, the abundance and composition of phytoplankton may also vary seasonally (Friese et al., 2014). Seasonal dynamics, therefore, play a crucial role in nutrient processing and retention efficiency. Usual monitoring programs at monthly or biweekly sampling can resolve such seasonal dynamics although they fail to resolve processes at the event scale. The long time series involved in our study enabled us to detect dominant seasonal patterns. Yet, achieving a more thorough understanding of short-term dynamics, including the analysis of extreme events, necessitates significantly higher sampling frequencies. A study by Kong et al. (2019) using high-resolution online monitoring showed that retention dynamics can change at the scale of a few hours in small, highly flushed reservoirs like pre-dams.

The highest monthly SRP and TP retention efficiencies were observed during summer (Fig. 4) when elevated solar radiation, water temperature, and HRT support algal growth, nutrient uptake, and sedimentation. Such higher retention efficiency in the warm season has been also found by others (Determann et al., 2024; Habi et al., 2010; Paul, 2003; Paul et al., 1998; Pütz and Benndorf, 1998; Salvia-Castellvi et al., 2001). Similarly, the lower retention during winter, when the P-input is high, was expected since pre-dams have limited efficiency due to low light intensity, low temperature, and high discharge (Pütz and Benndorf, 1998). The patterns for Si and $NO_3$ retention peaked in late summer but showed similarities with the findings of Kong et al. (2019) where winter months often exhibit negative N retention (source of N due to mineralization), while summer months show positive retention (acting as a sink for N). Results shown in Fig. 4 also agree with Li et al. (2010) who concluded that the highest SRP removal took place when the current velocity in the water body was low so that settling could take place undisturbed. This also corroborates with Hülsmann et al. (2021) who indicated a pronounced reduction in the elimination of suspended particles and P during flood events characterized by high flushing rates.

Given these clear and well-explainable seasonal patterns in retention efficiency, we also noted that in many cases times with high loads coincide with low retention efficiencies. This happens, for instance, when high discharges during snowmelt come along with high nutrient load. At that time of the year, radiation and temperatures are still low, and retention efficiency, as well. But if the total load retained in the pre-dam is calculated (inflow load times retention efficiency), in fact, maximum absolute retention may occur outside the warm season. All this depends on the seasonal patterns in discharge, loads, and meteorological conditions. Nevertheless, pre-dams enable substantial nutrient retention during the warm season and this service can and should be exploited in surface water quality management.

## 5. Conclusion

Our results suggest that pre-dams provide a substantial ecosystem service in retaining nutrients and by that help to protect the downstream reservoir system from point and non-point load sources. Retention of phosphorus is particularly high and is overall about 40 %. Corresponding values for $NO_3$, and Si are lower (15.3 % and 15.9 %). We also learned that different load calculation methods achieve similar outputs for long time series (but UA underperformed). Furthermore, the pre-dam HRT and mean depth were identified as the main retention efficiency drivers. Our evaluation of pre-dams also indicates that regular hydrological and water quality monitoring of inflows and outflows is important for their management and performance evaluation. Further studies would benefit from nutrient monitoring at higher temporal resolution and could focus on quantifying the beneficial effects for the downstream water bodies.

## CRediT authorship contribution statement

**Taynara Fernandes:** Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tom Shatwell:** Writing – review & editing, Software, Methodology. **Martin Schultze:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Chenxi Mi:** Writing – review & editing, Data curation. **Maria Determann:** Writing – review & editing, Data curation. **Karsten Rinke:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

## 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.

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## Supplementary materials

Supplementary material associated with this article can be found in the online version, at doi:10.1016/j.watres.2024.122864.

## Data availability

The authors do not have permission to share data.

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