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A framework to develop joint nutrient criteria for lake eutrophication management in eutrophic lakes

Zhongyao Liang [a], Yaoyang Xu [b], Qianlinglin Qiu [b], Yong Liu [c,*], Wentao Lu [d,*], Tyler Wagner [e]

[a] Pennsylvania Cooperative Fish and Wildlife Research Unit, 407 Forest Resources Building, Pennsylvania State University, University Park, PA 16802, USA
[b] Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China
[c] College of Environmental Sciences and Engineering, State Environmental Protection Key Laboratory of All Materials Flux in Rivers, Peking University, Beijing 100871, China
[d] Chinese Academy for Environmental Planning, Beijing 100012, China
[e] U.S. Geological Survey, Pennsylvania Cooperative Fish and Wildlife Research Unit, Pennsylvania State University, 402 Forest Resources Building, University Park, PA 16802, USA

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ABSTRACT

Nutrient criteria provide the numeric basis for lake eutrophication management. However, there are two obstacles that can hinder the effective application of nutrient criteria, including 1) although total phosphorus (TP) and total nitrogen (TN) might co-limit phytoplankton biomass in eutrophic lakes, their criteria are often developed independently; and 2) the linkage between nutrient criteria and the percentile-based compliance assessment method of chlorophyll *a* (CHL; as a measure of phytoplankton biomass) has not been well established. To resolve these obstacles, we propose a novel analytical framework of nutrient criteria development, by which joint nutrient criteria are developed using quantile regression (QR). We demonstrated the steps necessary to utilize this novel approach using TP, TN, and CHL data from Lake Dianchi, a hypereutrophic lake located in southwestern China. First, we built candidate QR models to quantify the nutrient-CHL relationship at six regression quantiles. Next, we conducted the sequential Wald test to select the "best" model for each regression quantile. Finally, we visualized the joint nutrient criteria surface using a contour map. The contour map effectively illustrated the joint nutrient criteria by showing the linkage of TP and TN criterion. In addition, based on the QR, it was easy to deduce nutrient criteria which met the requirement of percentile-based compliance assessment. We further found that joint nutrient criteria could help the selection of an efficient load reduction strategy in the watershed. The proposed method can be generalized to other systems and may facilitate site-specific lake eutrophication management.

1. Introduction

Nutrient criteria provide the numeric foundation for lake eutrophication management (Heiskary and Bouchard, 2015), particularly for curbing excessive phytoplankton biomass (Soranno et al., 2008) and informing watershed load reduction strategies (Poikane et al., 2019). While other factors, such as water temperature, could impact the growth of phytoplankton, nutrients are relatively more manageable through actions like watershed load reduction (Paerl et al., 2011). Nutrient criteria are mainly deduced from the nutrient-Chlorophyll *a* (CHL, as a measure of phytoplankton biomass) relationship by identifying critical nutrient concentrations that result in a target CHL concentration (Freeman et al., 2009; USEPA, 2010; Bachmann et al., 2012; Huo et al., 2013). In fact, a substantial amount of work has been conducted to develop total phosphorus (TP) and total nitrogen (TN) criteria for inland lakes (Heiskary and Wilson, 2008; Herlihy et al., 2013; Huo et al., 2018).

Although many informative studies have been performed on the development of nutrient criteria, there are two obstacles hindering effective application of nutrient criteria to lake eutrophication management. The first one is that, although CHL might be co-limited by TP and TN in eutrophic lakes (Filstrup and Downing, 2017; Wurtsbaugh et al., 2019), there is a lack of linkage between TP and TN criterion. Current criterion development of one nutrient based on the stressor-response model is often independent and without consideration of the

* Corresponding authors.
E-mail addresses: zvl5373@psu.edu (Z. Liang), yyxu@iue.ac.cn (Y. Xu), llqq@iue.ac.cn (Q. Qiu), yongliu@pku.edu.cn (Y. Liu), luwt@caep.org.cn (W. Lu), txw19@psu.edu (T. Wagner).

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other (Liu et al., 2018; Poikane et al., 2019; Tong et al., 2019; Huo et al., 2019). That is, the TP criterion is deduced based on the TP-CHL relationship, while the TN criterion is deduced using the TN-CHL relationship. However, it has been recognized that TP and TN should often be simultaneously considered as predictors in the nutrient-CHL relationship (Malve and Qian, 2006; Liang et al., 2019). Therefore, the effectiveness of a nutrient criterion deduced from a single nutrient-CHL relationship may be highly uncertain. Moreover, there might be a significant interaction between TP and TN on CHL, which would be missed when developing an independent criterion (Kotamäki et al., 2015; Qian et al., 2019). Failure to account for such a significant interaction may result in biased parameter estimates and might lead to an improper nutrient criterion.

The second obstacle is that the linkage between nutrient criteria and the compliance assessment of CHL has not been well established (Scott and Haggard, 2015). To curb lake eutrophication, an important goal is to reduce CHL to a specific target level. The compliance assessment of CHL is essential to evaluate the achievement of lake eutrophication management. In practice, the compliance assessment metric has long been an upper percentile of water quality variables (Mcbride and Ellis, 2001; Borsuk et al., 2002; Qian et al., 2015; Smith and Canale, 2015). For example, Walker (1984) proposed a compliance assessment method based on the frequency of CHL exceeding a specific level. The U.S. Environmental Protection Agency guidelines require a waterbody to be listed as impaired when more than 10% of the samples violate the standard (Smith et al., 2001), indicating that the 90% quantile of samples is used to compare with the standard. Generally, the assessment of an upper percentile is a more conservative way than that of the average, and in the meanwhile, allows for the violation of a small proportion of samples (Gibbons, 2003). Such an assessment method could provide information on the noncompliance probability of water quality variables (Liang et al., 2017). Moreover, the upper percentile of CHL is more related to some extreme conditions (e.g. algal bloom) than the average CHL and thus can better inform lake eutrophication management (Ostrofsky and Rigler, 1987; Jones et al., 2011).

While the compliance assessment method of CHL is percentile-based, current nutrient-CHL relationships are often developed using mean regression methods (e.g. linear regression or random forest) (Xu et al., 2015; Tong et al., 2019). Common practices of mean regression methods often focus on the average CHL concentration (Heiskary and Wilson, 2008; Trebitz, 2012; Tong et al., 2019; Liang et al., 2020), which would guarantee the compliance of average CHL, but might not meet the requirement of the percentile-based compliance assessment. Note that the percentile of CHL concentration could also be obtained using a mean regression method (Borsuk et al., 2002; Malve and Qian, 2006; Gronewold et al., 2008). However, its accuracy heavily relies on meeting the homoscedasticity assumption (Cade and Noon, 2003; Das et al., 2019). The log-transformation has been successfully used to accommodate this assumption (Oliver et al., 2017; Wagner and Schliep, 2018; Liang et al., 2019), but this may not guarantee homoscedasticity for all cases.

In this study, we propose a novel analytical framework for nutrient criteria development. In the framework, we 1) propose joint nutrient criteria to reflect the linkage of TP and TN criterion for determining target CHL levels; and 2) employ quantile regression (QR) (Koenker and Bassett, 1978) to illustrate the nutrient-CHL relationship to bridge the gap between nutrient criteria and the percentile-based CHL compliance assessment method. QR explores the effect of predictor(s) on any interested quantiles of the response (Das et al., 2019). Compared with mean regression, QR is robust to outliers in the response, requires no assumptions on the distribution of the response, and provides a more complete view of the relationship between predictor(s) and response variables (Cade and Noon, 2003; Das et al., 2019). Although QR has been used in ecological studies for about two decades (Cade et al., 1999), it has only recently been applied to illustrate nutrient-CHL relationships (Xu et al., 2015) and has rarely been used in nutrient criteria development. To demonstrate steps of the proposed framework, we used TP, TN, and CHL data from a hypereutrophic lake (Lake Dianchi, China) as a case study. We further discuss applications of the proposed joint nutrient criteria to lake eutrophication management.

2. Materials and methods

2.1. Study area

Lake Dianchi (24°29′N–25°28′N, 102°29′E–103°01′E) is located on Yunnan-Guizhou Plateau, southwest China. It is a shallow lake with the mean depth of 4.4 m. The lake area is approximately 309 km^2. The east to west distance of the lake is 7 km and the north to south distance is 40 km. The watershed is in a subtropical moist monsoon zone, with an average annual precipitation of approximately 1,000 mm and an average air temperature of approximately 14.5°C.

Lake Dianchi is located in the lower part of the watershed and receives both point (wastewater) and non-point sources of nutrients. The lake is facing a severe eutrophication problem that has spanned the past two decades (Liang et al., 2018), and therefore it is critical to develop reasonable nutrient criteria to inform eutrophication management. Long-term (January 1999–June 2019) monthly observations of TP, TN, and CHL from eight sites were used for this analysis. Data are from the Environmental Monitoring Site of Yunnan Province (http://www.ynsem.com.cn/). There are few (32) missing values, which were interpolated using the median polish method following Qian et al. (2000). The average TP, TN, and CHL concentrations during our research period are 0.160 mg/L, 2.04 mg/L, and 0.069 mg/L, respectively, showing the hypereutrophic state of Lake Dianchi.

2.2. Joint nutrient criteria development and modeling

In this study, we focus on the criteria development of TP and TN. It is worth noting that some active forms of nutrients, e.g. dissolved inorganic nitrogen and phosphate, are more directly related to algal growth and the criteria development of other nutrient forms could also be important (Yang et al., 2019). However, the development of reliable site-specific nutrient criteria requires a relatively long-term data set. The development of criteria of other nutrient forms is thereby often constrained by the lack of necessary data.

Examination of the scatter plots between TP and TN versus CHL (Figure S1), indicates that linear QR is appropriate for illustrating the nutrient-CHL relationship in Lake Dianchi. The main function of the linear QR (Eq. 1) is shown below:

$$y_i = \theta_0 + \theta X_i + \epsilon_i \tag{1}$$

where i is the rank of observations ($i = 1, 2, \ldots, N$, N is the sample size), y represents the response (CHL), and X represents the predictor(s) (TP and/or TN). θ_0 and θ represent the regression intercept and slope(s). ϵ is the error. Unlike ordinary least squares, which estimates parameters by minimizing the residual sum of squares (Altman and Krzywinski, 2015), the parameters estimation in linear QR is based on the minimum of weighted absolute biases (Eq. 2) (Koenker and Bassett, 1978):

$$\min\left[\sum_{i\in\{i:y_i\geqslant\theta X_i\}}\tau|y_i-\theta_0-\theta X_i| + \sum_{i\in\{i:y_i<\theta X_i\}}(1-\tau)|y_i-\theta_0-\theta X_i|\right] \tag{2}$$

where τ represents the quantile of the response.

Effects of nutrients at several upper quantiles of CHL were explored ($\tau = 0.5, 0.6, 0.7, 0.8, 0.9, 0.95$). While the QR is robust to outliers of the response (CHL), observations with very high or very low values of predictors (TN and TP) can influence the relationship. For example, a small number of observations with high nutrient concentrations but low CHL concentrations can easily change the shape of the regression curve. Because these observations only account for a small proportion of the total observations and do not span the entire distribution of CHL, their impact on the relationship can be substantial. For the purpose of nutrient criteria development, we do not have to pay much attention to these more "extreme" observations, because model extrapolation is not required. As such, we selected observations with nutrient concentrations in the range of their 10%–90% quantile. The final sample size is 1306 observations of TP, TN, and CHL. The proposed framework for joint nutrient criteria development has three steps (Fig. 1).

The first step is to develop candidate models that represent potential nutrient-CHL relationships. In our case, we developed five candidate models that represent hypotheses of how CHL responds to TP and TN. The first model (Model 1) was developed according to the common practice of illustrating the nutrient-CHL relationship using mean regression (Malve and Qian, 2006). In this model, main effects of TP, TN, and their interaction term were included (this was an effects-parameterized regression that included an intercept term). For a mean nutrient-CHL regression, a log–log linear model is typically fitted to accommodate the normality and homoscedasticity assumptions (Oliver et al., 2017). However, QR is not constrained by the above assumptions and the log-transformation is not necessary. Theoretically, when nutrients concentrations approach zero, the CHL concentration should also be near zero (Heiskary and Bouchard, 2015). Thus, we also developed a candidate model without the intercept term (Model 2). Some studies have also revealed that the interaction term might not be important (Liang et al., 2018), so the third candidate model lacked an interaction term. Lastly, we considered single nutrient limiting conditions and developed candidate models four and five for TP and TN, respectively. A summary of the candidate models is shown in Table 1.

The second step is to fit the models and perform model selection to obtain the "best" model for describing the nutrient-CHL relationship. For each candidate model, there were six quantiles to fit, resulting in a total of 30 QR models. A modified version of the Barrodale and Roberts algorithm for l_1-regression was used for parameters estimation (Koenker and D'Orey, 1987). After parameter estimation, we selected the "best" model for each regression quantile using a sequential Wald test. The Wald test is a commonly used method for nested model comparison (Koenker and Bassett, 1982) and tests the null hypothesis that less complex models with fewer estimated parameters are adequate relative to the largest specified model (full model). Using the sequential Wald test, we first test all five models, by which Model 1 is the full model. If the performances of all the four simpler models, candidate model 2–5, are significantly worse than the full model as indicated by sequential Wald test results, then the full model should be selected as the "best" model and the sequential test terminates. Otherwise, Model 1 is removed, and Model 2 becomes the full model for comparing the remaining models. This process is repeated until the "best" model is identified. Moreover, we applied joint Wald test to examine the equality of slopes, which could indicate the whether the homoscedasticity assumption is violated or not for a mean regression method.

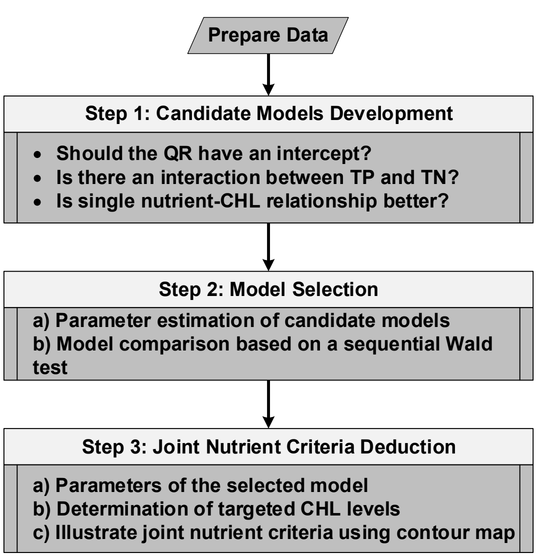

Fig. 1. Steps to implement the framework for joint nutrient criteria development using quantile regression.

Table 1
Candidate models to illustrate the nutrient-CHL relationship in Lake Dianchi. In the model formula, expressions show predictor structures to predict CHL, "−1" means the regression equation has no intercept.

Model #	Formula	Description
1	TP + TN + TP × TN	TP and TN have significant effect on CHL. Interactive effect and intercept are also significant.
2	TP + TN + TP × TN−1	TP and TN have significant effect on CHL. Interactive effect is significant. Intercept is not significant.
3	TP + TN−1	TP and TN have significant effect on CHL. Neither interactive effect nor intercept is significant.
4	TP−1	Only TP has significant effect on CHL. Intercept is not significant.
5	TN−1	Only TN has significant effect on CHL. Intercept is not significant.

After model selection, the third step is to deduce the joint nutrient criteria. We first select several target CHL levels. Then, we determine the joint nutrient criteria using the estimated parameters from the best nutrient-CHL relationship. The deduced nutrient criteria were reflected by an expression between TN and TP. Because the joint nutrient criteria are 2-dimensional and difficult to show in a table, the final step is to illustrate the joint nutrient criteria using a contour map (Fig. 1). The contour map is an effective way to show the nutrient-CHL relationship when both TN and TP are used as predictors (Malve and Qian, 2006; Yuan and Pollard, 2015; Liang et al., 2019). Note that if the selected model has only one nutrient as the predictor, the contour map is not required.

2.3. Single nutrient criterion development

To compare the joint nutrient criteria and the single nutrient criteria, we also developed single nutrient criterion. Following common practices of single nutrient criterion development (Huo et al., 2013), we fitted log–log linear nutrient-CHL relationship to deduce the single nutrient criterion:

$$\log(y_i) = \beta_0 + \beta \log(x_i) + \varepsilon_i \tag{3}$$

where i is the rank of observations ($i = 1, 2, \ldots, N$, N is the sample size), $\log(y)$ represents the log-transformed CHL observation, and $\log(x)$ represents the log-transformed TP or TN observation. β_0 and β represent the regression intercept and slope(s). ε is the error. Note that Eq. 3 is similar to Eq. 1, but Eq. 3 only includes one nutrient as the predictor, while Eq. 1 could have more predictors.

All the computations were conducted using the R software (R version 3.6.1) (R Core Team, 2019). The algorithm for parameter estimation of QR models was implemented using the `rq` function in the `quantreg` package (Koenker et al., 2019). The sequential and joint Wald tests are based on the `anova` function in the `quantreg` package. The code for the development of QR and model selection can be found at https://doi.org/10.5281/zenodo.3956328.

3. Results

3.1. Model selection and parameter estimation

Model selection results are shown in Table 2. The best models were

Table 2

Results of model selection based on the sequential Wald test and parameter estimates of selected models at five regression quantiles. Mean and standard error (subscript) of regression parameters are shown. All parameters are significant ($p < 0.05$). "–" represents the model does not include the model term. Refer to Table 1 for the formula and description of each model.

Quantile	Model number	Parameters			
		intercept	slope: TP	slope: TN	interaction
0.5	3	–	$0.237_{0.0250}$	$0.013_{0.0017}$	–
0.6	3	–	$0.271_{0.0294}$	$0.014_{0.0019}$	–
0.7	3	–	$0.304_{0.0294}$	$0.017_{0.0019}$	–
0.8	2	–	$0.493_{0.0544}$	$0.019_{0.0025}$	$-0.071_{0.0242}$
0.9	2	–	$0.603_{0.0798}$	$0.027_{0.0042}$	$-0.123_{0.0352}$
0.95	2	–	$0.721_{0.1219}$	$0.034_{0.0061}$	$-0.157_{0.0736}$

either models 2 or 3, depending on the quantile. The addition of the intercept did not significantly improve model performance, supporting the common view that when nutrient concentrations are zero, the CHL concentration should also be zero (Heiskary and Bouchard, 2015). In addition, model selection indicated that both nutrients were important predictors of CHL and therefore should be included as predictors for all the regression quantiles evaluated.

The estimated parameters for the effects of TP and TN across the different quantiles indicate that the response of CHL per unit increase in TP or TN is greater at higher regression quantiles (Table 2). The interaction term for TP and TN was not significant for lower quantiles (τ = 0.5, 0.6, 0.7) and was more likely to be significant at upper quantiles (τ = 0.8, 0.9, 0.95). The significant interaction terms were negative, indicating that the increase of one nutrient would lower the effect of the other nutrient on CHL, which agrees with previous work using mean regression (Qian et al., 2019). The magnitude of the interaction term was larger at a higher quantile, indicating an increasing interactive effect with increasing regression quantile.

3.2. Joint nutrient criteria

Contour maps (Fig. 2) illustrate the deduced nutrient criteria. In the contour map, *x*- and *y*- axes represent TP and TN, respectively, and isolines represent a range of target CHL concentrations. As regression quantiles increase, isolines move toward the lower left of the plots, indicating stricter nutrient criteria at higher regression quantiles. Isolines in Fig. 2(d)–(f) are curvlinear, illustrating the interactive effect of TP and TN on CHL. We explored joint nutrient criteria for six target CHL concentrations at six regression quantiles. In practice, however, if the target CHL and the regression quantile are determined, joint nutrient criteria can be simply shown by a single isoline. For example, if the target CHL is 0.08 mg/L and the regression quantile is 0.9, the corresponding joint nutrient criteria is the green curve in Fig. 2(e).

4. Discussion

4.1. Incorporating the linkage between TP and TN criterion

The joint nutrient criteria incorporate the linkage of TP and TN criterion via the inclusion of both nutrients as predictors in the nutrient-CHL relationship. Joint nutrient criteria simultaneously reflect effects of both nutrients on CHL. As shown by the contour map, for a certain target CHL level, the criterion for one nutrient may be dependent on the concentration of the other nutrient (Fig. 2). This is the most notable feature of joint nutrient criteria compared with the development of single nutrient criterion, where the nutrient criterion is invariant across concentrations of other potentially limiting nutrients.

Moreover, there might be biases between joint nutrient criteria and nutrient criteria deduced from the single nutrient-CHL relationship. We fitted QR models with only one nutrient as the predictor (Model 4 and 5 in Table 1) and then calculated the nutrient criteria by setting the target CHL concentration to be 0.08 mg/L and by setting the quantile to be 0.9, respectively. In Fig. 3, the deviation of the point from the isoline in the same color shows the bias between the two types of nutrient criteria. As we can see, in a few cases, the point matches with the isoline, indicating that the single nutrient criterion might be consistent with the joint

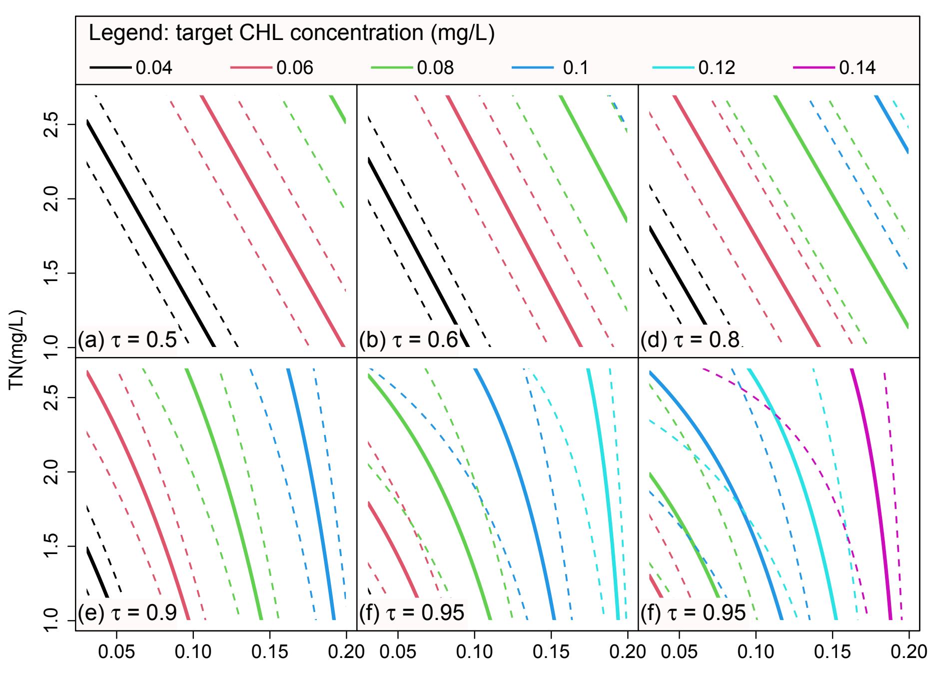

Fig. 2. Percentile-based joint nutrient criteria for target CHL concentrations at different regression quantiles (τ). *x*- and *y*-axes represent TP and TN, respectively, and isolines represent a range of target CHL concentrations. Dashed lines are ±1 standard deviation.

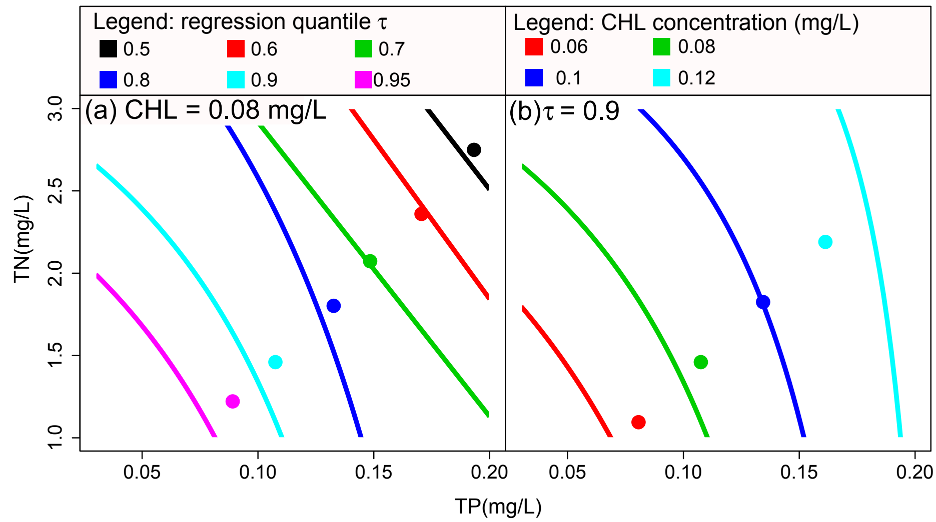

Fig. 3. Comparison of percentile-based joint nutrient criteria (isolines) and nutrient criteria deduced from the single-nutrient relationship (points). In the left panel (a), we set the target CHL concentration to be 0.08 mg/L and nutrient criteria for different regression quantiles are identified by the color. In the right panel (b), we set the regression quantile to be 0.9 and nutrient criteria for different CHL levels are identified by the color.

nutrient criteria. However, the bias exists for most cases (Fig. 3), emphasizing the necessity of including both nutrients in the nutrient-CHL relationship. Besides, the joint nutrient criteria provide many combinations of TP and TN criterion, while the single nutrient criterion only has one combination.

4.2. Advantages of using quantile regression

The main advantage of applying QR is to bridge the management gap between nutrient criteria and compliance assessment. Based on the QR, we easily obtain the joint nutrient criteria given the target CHL concentration and the regression quantile. The regression quantile is consistent with the percentile of the compliance assessment. Suppose that the percentile is τ for the compliance assessment, the deduced nutrient criteria aim to make the τ^{th}-quantile of CHL meet the standard. The QR can easily accommodate water quality compliance assessments with different percentiles. Therefore, QR makes the nutrient criteria development in harmony with the compliance assessment, which could facilitate effective lake eutrophication control practices.

In contrast, nutrient criteria deduced by mean regression might give ambiguous information for the percentile-based compliance assessment. For example, we fitted the log–log linear nutrient-CHL relationship for TP and TN, respectively. Then, we calculated the corresponding criteria setting the target CHL to be 0.04 mg/L, 0.06 mg/L, and 0.08 mg/L. We found that the combination of these nutrient criteria would locate between isolines of 0.7–0.8 quantile (Fig. 4(a)), isolines of 0.6–0.7 quantile (Fig. 4(b)), and around the isoline of 0.5 quantile (Fig. 4(c)), respectively. That is, probabilities of CHL exceeding corresponding targets are between 0.2 and 0.3, between 0.3 and 0.4, and about 0.5, respectively. This discrepancy in noncompliance probability makes it difficult to meet the requirement of percentile-based compliance assessments using the nutrient criteria deduced from mean regression.

Although QR has advantages and intuitive appeal for developing criteria, some mean regression methods, such as linear regression, could also be used to deduce the quantile of CHL concentrations (Borsuk et al., 2002; Malve and Qian, 2006; Gronewold et al., 2008) and thereby are potentially capable of quantile-based nutrient criteria. In such studies, the log–log linear nutrient-CHL relationship was first built using a mean regression method, and then the distribution of CHL was obtained. Note that the accuracy of the quantile estimation relies heavily on the

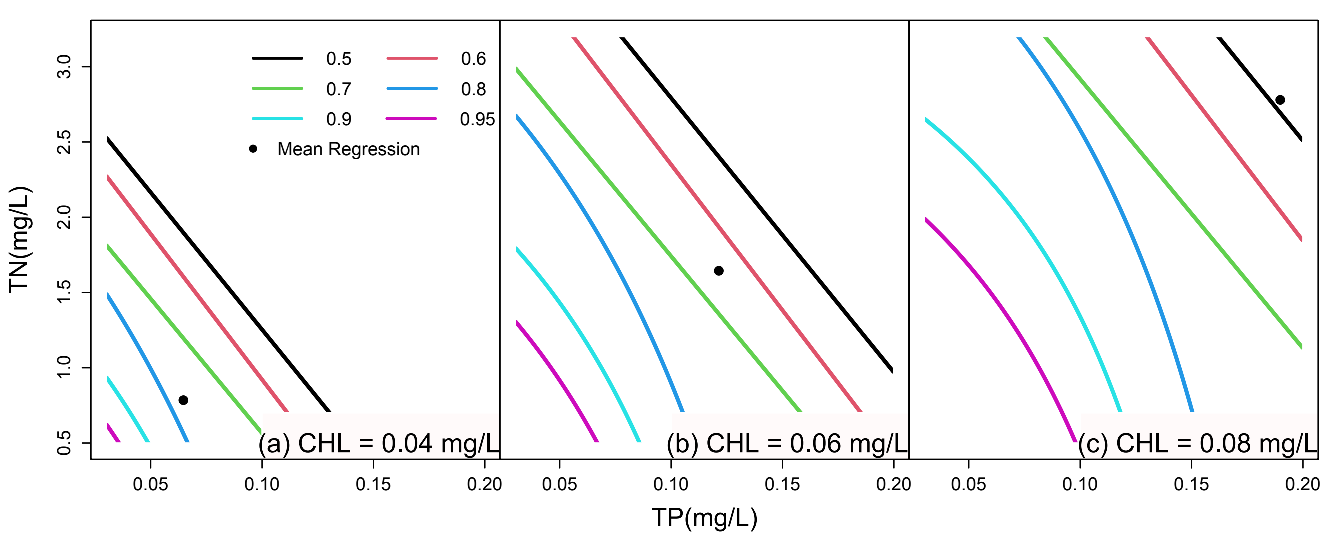

Fig. 4. Comparison of joint nutrient criteria and single nutrient criterion given different target CHL concentrations. The isolines are joint nutrient criteria under different regression quantiles. The black point represents the combination of TP and TN criterion deduced from the single nutrient-CHL relationship (Eq. 3).

homoscedasticity assumption in mean regression methods, which might be violated. An effective tool to test the violation is to examine the regression slopes of QR models for a range of regression quantiles (Das et al., 2019). If slopes are significantly different, then the mean regression method might be inadequate and the deduced nutrient criteria might be misleading. In our case, we examined the QR slopes of TP, TN, and interactive term for nine symmetrical regression quantiles (0.1, 0.2, …, 0.9). The observations were log-transformed following common practices of building nutrient-CHL relationship (Borsuk et al., 2002; Malve and Qian, 2006; Gronewold et al., 2008). A joint Wald test (Koenker et al., 2019) was employed to test the equality of slopes at different regression quantiles and showed the inequality of slopes ($p < 0.05$). Therefore, the mean regression method is not adequate to estimate percentiles of CHL concentration in our case.

There may be occasions where using mean regression methods to predict the percentile of CHL concentration is adequate. However, above results suggest that this should be done with caution. It would be useful to examine the equality of slopes for a range of regression quantiles using QR prior to applying mean regression. If the equality of slopes is confirmed, then nutrient criteria could be deduced. Otherwise, using mean regression is not suitable due to the possibility of violation of the homoscedasticity assumption. In contrast, the usage of QR is much more convenient, intuitive, and reliable.

4.3. Informing watershed load reduction

Joint nutrient criteria can also inform the selection of an efficient watershed load reduction strategy. TP and TN loads are often simultaneously reduced by watershed load reduction actions, e.g., via wetlands (Fisher and Acreman, 2004), sewage treatment plants (Boynton et al., 2008), and best management practices (Qiu et al., 2018). In addition, TP and TN are also highly coupled in lake ecosystems (Oliver et al., 2017; Aubriot, 2018). In practice, through the modelling of nutrient dynamics in the watershed and waterbody using a water quality model, the effect of a load reduction strategy on nutrient concentrations can be quantified (Dai et al., 2018) and the concentration reduction curve (red or blue curve in Fig. 5) could be obtained. For example, suppose the effect of a load reduction strategy on nutrient concentrations is the blue line in Fig. 5a) and the aim of load reduction is to make the probability of CHL exceeding 0.08 mg/L less than 10%. The green lines in Fig. 5 shows joint nutrient criteria when the target CHL concentration is 0.08 mg/L and the regression quantile is 0.9 (the same as the green isoline in Fig. 2(e)). Point A shows the current combination of TP and TN concentrations. The intersection of the effect curve of load reduction strategy and joint nutrient criteria (point B in Fig. 5(a)) shows expected nutrient concentrations when CHL meets the standard, based on which we can calculate the cost (e.g. required time or money) to get from point A to point B. Suppose now we have another load reduction strategy and its effect curve is the red line in Fig. 5(a). We can also calculate the corresponding cost to get from point A to point C and compare the two strategies.

By contrast, the form of current nutrient criteria might lead to extra cost of load reduction. Current nutrient criteria consist of one TP criterion and one TN criterion, and thus could be presented as a point in Fig. 5, such as point D or E in Fig. 5(b). Suppose point D is the deduced nutrient criteria and the blue line is the effect curve. We found that to meet the requirement of the nutrient criteria, we would need to keep taking management actions until the nutrient concentrations reduce to point G, so that both nutrient concentrations are not larger than that of point D. But, in fact, CHL should meet the requirement at point B. Extra cost is paid from point B to point G. If point E is the deduced nutrient criteria, extra cost is paid from point B to point F.

4.4. Generalization of joint nutrient criteria

Considering the mismatch between ecoregional and site-specific nutrient-CHL relationships (known as ecological fallacy) caused by the heterogeneity of ecological contexts (Qian et al., 2019; Liang et al., 2020), there is a need for the development of site-specific nutrient criteria (Olson and Hawkins, 2013; Liang et al., 2020). We have demonstrated that the proposed joint nutrient criteria development framework could reasonably link the TP and TN criterion, bridge the management gap between water quality compliance assessment method and nutrient criteria development, and further inform watershed nutrient load reduction. Although our study focuses on a lake case study, we suggest that the proposed method and application of joint nutrient criteria could benefit site-specific lake ecosystem management more broadly for the following reasons:

1) The application of QR and corresponding model selection process are straightforward to implement in freely available statistical software, e.g., the R software as we used in this study.
2) Because CHL, TN, and TP data are widely available, the proposed method could be easily applied to other lakes.

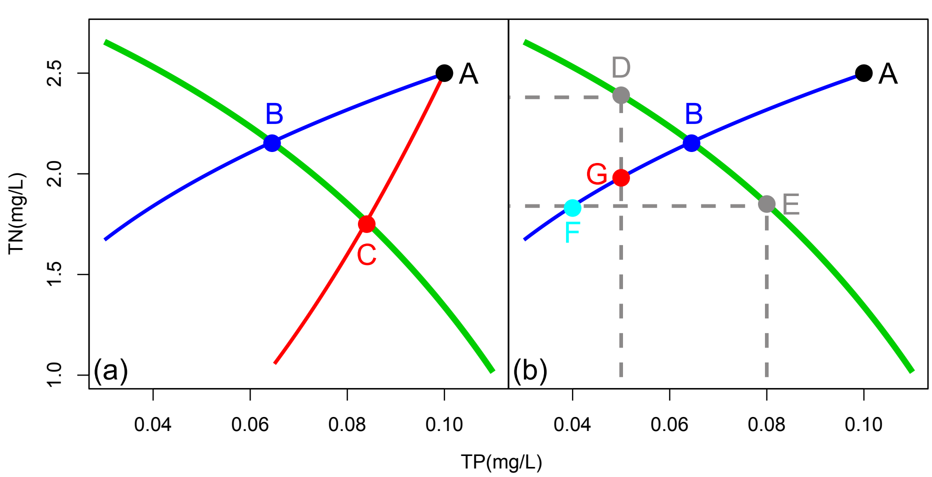

Fig. 5. Concept map showing how joint nutrient criteria help the selection of water load reduction strategy (a) and how current nutrient criteria form might lead to extra cost (b). The green isoline represent the joint nutrient criteria given a target CHL concentration and a regression quantile. The blue and red lines represent two paths of TP and TN concentration reduction due to eutrophication management actions. Each point represents a combination of TP and TN concentrations. The black point A represents the current state of TP and TN concentration, which is away from the required nutrient concentrations (the green line). Any point (B, C, D, & E) in the green line would meet the requirement of CHL concentration control. Point B and C represents the nutrients concentrations meeting the CHL concentration requirement of the blue and red paths, respectively. Point D and E represent the combination of single nutrient criteria. When the concentration reduction follows the blue line, if single nutrient criteria are development (point D or E), the required nutrients concentrations should be lower (point G or F) than those represented by point B, which would result in extra cost.

3) This approach can be applied using other forms of nutrients, which are often quantified in monitoring programs. Additional nutrient forms could be added as predictors and additional candidate models could be built in the first step of our approach. We can then determine which nutrient form(s) should be included via the model selection process in the second step. Finally, only nutrient forms that would significantly improve model performance would be included in the joint nutrient criteria. That said, careful consideration of what types of nutrient forms to include is prudent, since including too many nutrients into a joint nutrient criterion could make eutrophication management overly complicated.

4) Other management endpoints, such as algal communities (Smucker et al., 2013) or macroinvertebrate metrics (Wagenhoff et al., 2017), could also be chosen as the response, aiming to achieve an acceptable ecological status. Our method could also be extended to such cases, where nonlinear QR, such as additive non-parametric QR (Koenker et al., 1994), QR neural networks (Cannon, 2011), or QR forests (Meinshausen, 2006), might be required.

5. Conclusions

We proposed a novel analytical framework for the development of nutrient criteria and used Lake Dianchi, China as a case to illustrate the steps of the framework. The percentile-based joint nutrient criteria, as shown by the contour map, incorporate the dependencies between TP and TN criterion. The application of QR bridges the gap between nutrient criteria and the compliance assessment. We further found that joint nutrient criteria can help with the selection of a watershed nutrient load reduction strategy and believe that our approach can help inform site-specific lake eutrophication management. Our approach can also be generalized to other lakes, nutrient forms, and management endpoints.

CRediT authorship contribution statement

Zhongyao Liang: Conceptualization, Methodology, Software, Formal analysis, Resources, Writing - original draft, Writing - review & editing, Visualization. **Yaoyang Xu:** Methodology, Software, Writing - original draft, Writing - review & editing. **Qianlinglin Qiu:** Methodology, Software, Writing - original draft, Writing - review & editing. **Yong Liu:** Resources, Writing - original draft, Writing - review & editing. **Wentao Lu:** Writing - original draft, Writing - review & editing. **Tyler Wagner:** Formal analysis, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.jhydrol.2020.125883.

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