

## Developing a 21st Century framework for lake-specific eutrophication assessment using quantile regression

Yaoyang Xu,<sup>\*1</sup> Andrew W. Schroth,<sup>2</sup> Donna M. Rizzo<sup>3</sup>

<sup>1</sup>Vermont EPSCoR, University of Vermont, Burlington, Vermont

<sup>2</sup>Department of Geology, University of Vermont, Burlington, Vermont

<sup>3</sup>School of Engineering, University of Vermont, Burlington, Vermont

### Abstract

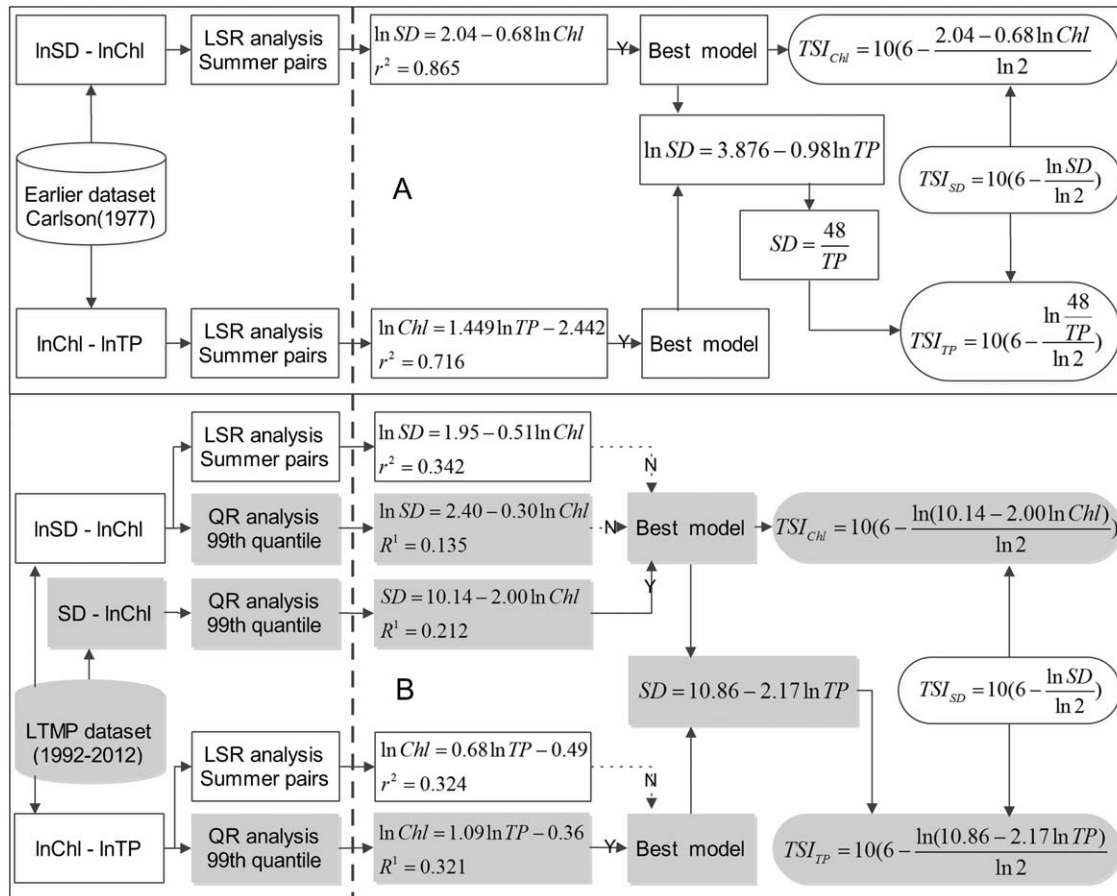
Over the past 30+ years, researchers and water resource managers have often relied on a set of regression-based equations to describe the relationships between secchi depth (SD), chlorophyll (Chl) and total phosphorous (TP) and quantitatively assess lake trophic status after Carlson (1977). Here, we develop a revised framework for eutrophication assessment that incorporates recent statistical advances in ecology and leverages the increasing availability of lake-specific datasets in the 21st Century. Long-term (1992–2012) water quality data from Lake Champlain (LC) are used to revisit and revise classic equations of trophic state indices ( $TSI_{Chl/TP}$ ). The upper boundaries of  $SD-\ln(Chl)$  and  $\ln(Chl)-\ln(TP)$  distributions within this dataset fit well with quantile regression (99th, QR) to generate LC-specific  $TSI_{Chl/TP}$  equations. Our results illustrate that Carlson (1977)'s original  $TSI_{Chl/TP}$  equations overestimate the trophic status of LC relative to LC-specific equations, and highlight the power of the QR-derived  $TSI_{Chl/TP}$  metric. We combine  $TSI_{SD}$  and  $TSI_{Chl}$  into one metric to indicate pseudoeutrophication and pseudomesotrophication of oligotrophic waters as well as pseudoeutrophication of mesotrophic waters to identify waters threatened by potential trophic shift. Additionally,  $TSI_{Chl}$  and  $TSI_{TP}$  were coupled as a complimentary dual metric to indicate potential risks of excessive phosphorus loading to oligotrophic and mesotrophic waters. With these dual metric schemes, we performed cluster analysis of 15 locations to spatially assess trophic status and phosphorous risks across LC. This study describes a relatively simple and robust approach for lake-specific status assessment, the structure of which can be broadly utilized within monitoring and research communities.

Lake eutrophication, the process by which excessive nutrient loading alters the lake ecosystems from clear macrophyte-dominated waters to turbid phytoplankton-dominated waters, has been identified as a primary water quality problem throughout the world for several decades (Scheffer et al. 2001; Dodds et al. 2009; Schindler 2012). Several policy-related frameworks (e.g., Water Framework Directive and Clean Water Act) have been built by intergovernmental organizations (e.g., European Union) and governments (e.g., United States) to mitigate eutrophication and restore lake ecosystems (Soranno et al. 2008; Carvalho et al. 2013). While such regulatory frameworks can provide recommendations for management decisions on multilakes/reservoirs at the regional scale, they may be insufficient in detail when applied to individual ecosystems at local and watershed scales, because the drivers of lake trophic status are spatially and temporally variable across ecosystems and environments (Smith and Schindler 2009; Wagner et al. 2011). As such, robust assessment and

monitoring of lake trophic status is a key step in developing science-based recommendations and management decisions for individual ecosystems.

As a starting point to trophic status assessment, Carlson (1977)'s work introduced a set of trophic state indices ( $TSI_{SD/Chl/TP}$ ) as functions of common water quality measurements (Secchi depth [SD], Chlorophyll [Chl], Total phosphorus [TP]). The derivation of these metrics is illustrated in the flow chart of Fig. 1A with relevant regression equations. The inherent simplicity of these original TSI equations made them popular for evaluating lake ecosystems (e.g., Matthew and Jones 2006; Sulis et al. 2011; Umbanhowar et al. 2011). For example, the Wikipedia dictionary defines Carlson (1977)'s index as “one of the more commonly used trophic indices,” and over 500 of the US Environmental Protection Agency's technical documents employ the original TSI equations when assessing lake trophic status. However, many studies have noted substantial variation in the empirical relationship between SD and Chl and Chl and TP (e.g., Mazumder and Havens 1998; Hoyer et al. 2002; Mooij et al.

\*Correspondence: yaoyang.xu@uvm.edu; yaoyangxu@gmail.com



**Fig. 1.** Carlson (1977)'s framework (A) and LC-specific framework (B) summarizing the methodology (the left of vertical dash line) and modeling results (the right of vertical dash line) for generating of  $TSI_{Chl/TP}$  equations. The "N" in the dash-line arrow indicates that the step is NOT applicable; while the "Y" in line arrow represents that the step is applicable (YES).

2010; Stow and Cha 2013), calling into question the direct application of Carlson's (1977) empirical equations and their derived TSI metrics across diverse lake ecosystems. In fact, deviations between the TSI metrics have been used recently by researchers, including our own group, to infer lake dynamics using a simple graphical approach (Carlson and Havens 2005; Xu et al. 2010, 2011). In these studies, the TSI metric deviations describe abiotic and biotic relationships, as well as infer lake trophic structure and function (James et al. 2009; Xu et al. 2010, 2011). However, this approach may be problematic given that the relationships between SD, Chl, and TP and their deviations are derived from Carlson (1977)'s empirical equations, but those empirical relationships, and associated deviations of those metrics, are not necessarily appropriate when applied to specific individual lake ecosystems. Indeed, despite the common and diverse application of Carlson (1977)'s original TSI indices, few attempts have been made to develop a more robust framework for trophic status assessment in the context of recent statistical advances and the widespread availability of

ecosystem-specific long-term water quality datasets in the 21st Century.

Given recent statistical advances in ecology, another component of Carlson (1977)'s empirical equations that warrants attention is the "lumping" of measurements within a single dataset, where the relationship between measured variables may be confounded or driven by unmeasured factors (Cade and Noon 2003). For example, a reduction in water clarity comprised of nonalgal turbidity (e.g., inorganic suspended particles and dissolved organic matter), can exert significant influence on the relationship between SD and Chl (Lind 1986; Swift et al. 2006). Variability in water clarity may be unexplained by the empirical linear relationship between SD and Chl, given that conventional analysis (i.e., linear least squares regression [LSR]) focuses on the mean of the response distribution as a function of the measured factor and cannot exclude the effect of the unmeasured factors (Cade and Noon 2003). Similarly, it is likely that linear regression fails to quantify the empirical relationship between Chl and TP across a range of environmental

**Table 1.** Statistics summary of SD (m), chlorophyll *a* (Chl, mg m<sup>-3</sup>) and total phosphorus (TP, mg m<sup>-3</sup>).

	N	Mean	Median	Std. D	Min	Max
SD	3545	3.7	3.8	1.9	0.2	10.1
Chl	3545	6.1	4.2	7.0	0.4	116.4
TP	3545	24.2	16.4	17.7	5.0	235.0

conditions, because phytoplankton biomass (measured as Chl) may be regulated by other variables such as climate (Brown et al. 2000; Huszar et al. 2006), other macro or micronutrients (Mooij et al. 2010) or hydrology (An and Park 2002). As opposed to general data “lumping” or ad hoc isolation of the upper bounds of water quality data (e.g., Carlson 1977; Jones and Hubbart 2011; Jones et al. 2011), quantile regression (QR) better quantifies possible causal relationships between ecological variables, as its statistical foundation is theoretically consistent with the ecological concept of limiting factors (Cade et al. 1999; Cade and Guo 2000; Cade et al. 2005). As such, QR provides stronger and more useful predictive models and should be employed to generate TSI metrics that are more representative of the trophic status across time and space in diverse lake ecosystems.

Using 15 long-term monitoring stations in Lake Champlain (LC) spanning a diverse array of hydrodynamic and biological environments as a case study, we provide a modified framework for generating lake specific TSI metrics that is motivated by the elegant simplicity of Carlson’s original work. The approach utilizes routine measurement of SD, Chl, and TP to monitor and describe lake trophic status. Because decades of extensive research investment and intense monitoring of the trophic status and phosphorus loading to LC have produced a well-characterized recurring ecosystem assessment (i.e., LCBP 2012), this long-term dataset is ideal for testing the utility of this relatively simple approach. If our revised framework identifies the same areas of concern previously characterized by years of extensive hydrodynamic and biogeochemical research across the limnologically diverse segments that constitute LC, this validation presumably lends confidence that this relatively straightforward approach will be useful for other threatened ecosystems, where intermittent monitoring of these few basic parameters may be the only resources available. Specifically, the objectives of this study are to:

1. Use linear regression to examine LC-specific empirical relationships of  $\ln SD = f(\ln Chl)$  and  $\ln Chl = f(\ln TP)$  of summer measurements to revisit the validity of Carlson (1977)’s empirical equation for lake-specific ecosystems.
2. Use QR to quantify alternative LC-specific empirical relationships of  $SD = f(\ln Chl)$  and  $\ln Chl = f(\ln TP)$  that develop more robust lake-specific  $TSI_{Chl}$  and  $TSI_{TP}$  equations.

3. Combine  $TSI_{SD}$  with the improved empirically derived  $TSI_{Chl}$  and  $TSI_{TP}$  indices as dual metrics to classify trophic states and identify phosphorus risks.
4. Perform multivariate analysis on the dual metrics generated by this historical dataset to spatially formulate trophic classifications and excessive phosphorus risks across the diverse, dynamic and extensively studied LC ecosystem.

**Materials and Procedures**

**Study area and data collection**

As part of the St. Lawrence drainage, LC experiences similar history in geology, ecology, and biology with the Great Lakes (Facey et al. 2012). The large basin area to lake surface ratio (19 : 1) makes the LC ecosystem vulnerable to exogenous processes which associated with anthropogenic activity, land-use and climate change (Smeltzer et al. 2012). Due to the complex bathymetry and extensive shoreline, the LC ecosystem is subject to diverse endogenous processes and is characterized as a variety of lacustrine habitats from deep oligotrophic areas to shallow bays that are highly eutrophic (Facey et al. 2012). Resource managers have divided LC into 13 segments (South Lake A, South Lake B, Port Henry Segment, Otter Creek Segment, Shelburne Bay, Main Lake, Burlington Bay, Mallett’s Bay, Cumberland Bay, Northeast Arm, St. Albans Bay, Isle LaMotte, and Missisquoi Bay; LCBP 2012) for the purpose of establishing target phosphorus concentrations, which is the primary nutrient of eutrophication concern for exogenous and endogenous processes. TP concentrations have generally been stable or increased during the last 20 years in most of these segments (LCBP 2012), and increased by 72% in Missisquoi Bay where Chl concentrations doubled over this period (Smeltzer et al. 2012). Some segments for phosphorus loading and eutrophication concern were Missisquoi Bay, St. Albans Bay, and the central Northeast Arm; other segments were oligotrophic and mesotrophic due to relatively low phosphorus (Levine et al. 2012; Smeltzer et al. 2012).

Our data were obtained from the LC Long-Term Water Quality and Biological Monitoring Program (LTMP), which has been operated by the Vermont Department of Environmental Conservation and the New York Department of Environmental Conservation from 1992 until now (VTDEC and NYDEC 2013). This program comprises a total of 15 sampling locations distributed throughout the lake, where limnological data are monitored twice per month from May to early November each year. This LTMP database is freely available for researchers, managers, and the public at: [http://www.vtwaterquality.org/lakes/htmlp\\_longterm.htm](http://www.vtwaterquality.org/lakes/htmlp_longterm.htm). We downloaded the 1992–2012 SD (m), chlorophyll *a* (Chl, mg m<sup>-3</sup>) and TP (mg m<sup>-3</sup>) data for all 15 sampling stations, resulting in 3545 observations (Table 1). Details of the sampling methods and data quality controls can be found in the

**Table 2.** The classifications of trophic states using the threshold values of  $TSI_{Chl}$  and  $TSI_{SD}$ .

$TSI_{Chl}$ values	Classifications	$TSI_{SD}$ values	Subclassifications
$TSI_{Chl} < 40$	Oligotrophic (O)	$TSI_{SD} < 40$	Oligotrophic (OOs)
		$40 \leq TSI_{SD} < 50$	Pseudomesotrophic (OMs)
		$TSI_{SD} \geq 50$	Pseudoeutrophic (OEs)
$40 \leq TSI_{Chl} < 50$	Mesotrophic (M)	$40 \leq TSI_{SD} < 50$	Mesotrophic (MMs)
		$TSI_{SD} \geq 50$	Pseudoeutrophic (MEs)
		$TSI_{SD} \geq 50$	Eutrophic (EEs)
$TSI_{Chl} \geq 50$	Eutrophic (E)		

published Quality Assurance Project Plan of LTMP (VTDEC and NYDEC 2013).

#### Revision of $TSI_{Chl}$ and $TSI_{TP}$ metrics

We revisited Carlson (1977)'s empirical approach (Fig. 1A) and applied a natural log-transformation to all  $n = 3545$  LC data and then performed linear LSR on the  $n = 1426$  summer observations to generate the summer empirical  $\ln SD = f(\ln Chl)$  and  $\ln Chl = f(\ln TP)$  relationships for LC (Fig. 1B). As an alternative to Carlson (1977)'s approach, our modified framework adopted QR to estimate what we refer to as *full* parameter models ( $\ln SD = b_0 + b_1 \ln Chl + \varepsilon$ ,  $SD = b_0 + b_1 \ln Chl + \varepsilon$  and  $\ln Chl = b_0 + b_1 \ln TP + \varepsilon$ ). To infer a goodness of fit to the upper boundary of the data distributions, coefficients of determination ( $R^1$ ) for 99th quantile were calculated as follow:  $R^1 = 1 - (SUM_{(F)} : SUM_{(R)})$ , where  $SUM_{(F)}$  is the sum of weighted absolute deviations minimized in estimating each of those *full* parameter models, and  $SUM_{(R)}$  is the sum of weighted absolute deviations minimized in estimating each of the corresponding reduced parameter models ( $\ln SD = b_0 + \varepsilon$ ,  $SD = b_0 + \varepsilon$  and  $\ln Chl = b_0 + \varepsilon$ ). A more detailed description of QR can be found in previous publications (e.g., Cade et al. 1999; Koenker and Machado 1999; Cade and Noon 2003). Furthermore, we applied best-fit models for the upper boundary to create LC-specific  $TSI_{Chl}$  and  $TSI_{TP}$  equations. A paired-sample  $t$  test was used to examine whether Carlson (1977)'s  $TSI_{Chl}$  and  $TSI_{TP}$  values overestimated LC trophic states relative to LC-specific  $TSI_{Chl}$  and  $TSI_{TP}$  values. Linear regressions and paired-sample  $t$  tests were performed with the SPSS 13.0 software; and QR used the quantreg package version 5.05 of R (Koenker et al. 2013; R Development Core Team 2014).

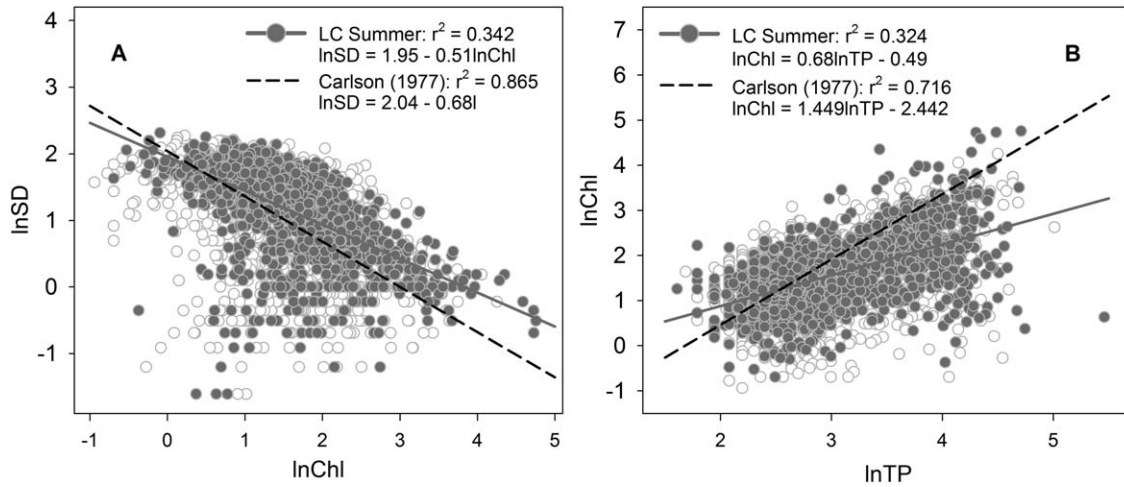
#### Trophic state classification and phosphorus risk identification

Using the threshold values of Carlson (1977)'s classification (Column 1 of Table 2), we employed the LC-specific  $TSI_{Chl}$  index to classify the trophic state for each LC observation as follows (Column 2 of Table 2): oligotrophic state (O), mesotrophic state (M), and eutrophic state (E). We performed paired-sample  $t$  tests to evaluate the significant differences of the  $TSI_{Chl}$ -based trophic state from the other two indices ( $TSI_{SD}$  and  $TSI_{TP}$ ). The  $TSI_{Chl}$ -based trophic state of each LC observation was further classified by the corresponding  $TSI_{SD}$  values into six trophic states (Columns 3 and 4 of Table 2): oligotrophic state (OOs), mesotrophic state (MMs), eutrophic state (EEs), pseudomesotrophic state (OMs), and pseudoeutrophic state (OEs) of oligotrophic observation as well as pseudoeutrophic state (MEs) of mesotrophic observation. If the trophic states classified by  $TSI_{SD}$  and  $TSI_{Chl}$  are consistent, they are defined as OOs, MMs, and EEs, indicating that algal biomass always dominates light attenuation and its reduction may improve water clarity. If the  $TSI_{SD}$ -classified states dramatically deviate from the  $TSI_{Chl}$ -based states, these states are characterized as pseudophenomena (OMs, OEs, and MEs) and nonalgal turbidity, rather than algal biomass, controls light attenuation. LC-specific  $TSI_{TP}$  values were employed to identify mesotrophic risk (OMp) and eutrophic risk (OEp) of excess phosphorus for the  $TSI_{Chl}$ -based oligotrophic state as well as eutrophic risk (MEp) of excess phosphorus for the  $TSI_{Chl}$ -based mesotrophic state (Table 3). When the  $TSI_{TP}$ -classified states are consistent with the  $TSI_{Chl}$ -based states, phosphorus limits algal biomass. Deviations of the  $TSI_{TP}$ -classified states from the  $TSI_{Chl}$ -based

**Table 3.** The identifications of phosphorus risks to mesotrophication and eutrophication with the critical values of  $TSI_{Chl}$  and  $TSI_{TP}$ .

$TSI_{Chl}$ values	Classifications	$TSI_{TP}$ values	Risk identifications
$TSI_{Chl} < 40$	Oligotrophic (O)	$TSI_{TP} < 40$	Oligotrophic (OOp)
		$40 \leq TSI_{TP} < 50$	Mesotrophic risk (OMp)
		$TSI_{TP} \geq 50$	Eutrophic risk (OEp)
$40 \leq TSI_{Chl} < 50$	Mesotrophic (M)	$40 \leq TSI_{TP} < 50$	Mesotrophic (MMp)
		$TSI_{TP} \geq 50$	Eutrophic risk (MEp)
		$TSI_{TP} \geq 50$	Eutrophic (EEp)
$TSI_{Chl} \geq 50$	Eutrophic (E)		





**Fig. 2.** Comparison between LC summer equations (solid gray line) and Carlson (1977)'s original equations (dashed black line) and of  $\lnSD = f(\lnChl)$  (A) and  $\lnChl = f(\lnTP)$  (B).

states (OMP, OEp, and MEp) indicate that excess phosphorus exists relative to current trophic state requirements.

#### Multivariate analysis for identifying spatial patterns

Based on the combined  $TSI_{Chl}$  and  $TSI_{SD}$  metrics (Table 2), we quantified the proportion of the six trophic states for each of the 15 sampling locations. We also combined the  $TSI_{Chl}$  and  $TSI_{TP}$  metrics (Table 3) to assess excess phosphorus risks for each of 15 sampling locations. Hierarchical cluster analysis (HCA), performed using PC-ORD 4.0 software (McCune and Mefford 1999), was used to group the 15 sampling locations into six trophic states and excess phosphorus risk, respectively.

## Results

#### Revision of $TSI_{Chl}$ and $TSI_{TP}$ metrics

LC-specific equations and TSI metrics generated by the revisited and modified framework (Fig. 1B) can be compared to those by Carlson (1977)'s original approach outlined in Fig. 1A. Based on the linear regression analysis of Carlson (1977), the modeled  $\lnSD$ - $\lnChl$  and  $\lnChl$ - $\lnTP$  scatter plots for the  $n = 1426$  summer observations produce the LC-summer equations  $\lnSD = 1.95 - 0.51\lnChl$  ( $r^2 = 0.342$ , Fig. 2A) and  $\lnChl = 0.68\lnTP - 0.49$  ( $r^2 = 0.324$ , Fig. 2B), respectively. QR showed that the intercept estimates increased with increasing quantiles for each of the full parameter models (Fig. 3A,D,G). The slope estimates for  $\lnSD = b_0 + b_1\lnChl + \varepsilon$  declined from 0 at the first to  $-0.57$  at the 16th quantile and then increased to  $-0.30$  at the 99th quantile (Fig. 3B), whereas the slopes for  $SD = b_0 + b_1\lnChl + \varepsilon$  gradually declined from 0 at the first quantile to  $-2.00$  at 99th quantile (Fig. 3E) and those for  $\lnChl = b_0 + b_1\lnTP + \varepsilon$  gradually increased from  $0.20$  at the first quantile to  $1.09$  at 99th quantile (Fig. 3H). When compared to the  $\lnSD = 2.40 - 0.30\lnChl$  (Fig. 3C), the  $SD = 10.14 - 2.00\lnChl$

(Fig. 3F) shows a substantial improvement in fit to the upper boundary. The  $\lnChl = 1.09\lnTP - 0.36$  exhibited a good fit to the upper boundary of  $\lnChl$  and  $\lnTP$  distribution (Fig. 3I).

Substituting the LC-99th quantile model ( $SD = 10.14 - 2.00\lnChl$ ) into  $TSI_{SD}$  equation, yields the following LC-specific  $TSI_{Chl}$  equation:

$$TSI_{Chl} = 10 \times \left( 6 - \frac{\ln(10.14 - 2.00\lnChl)}{\ln 2} \right)$$

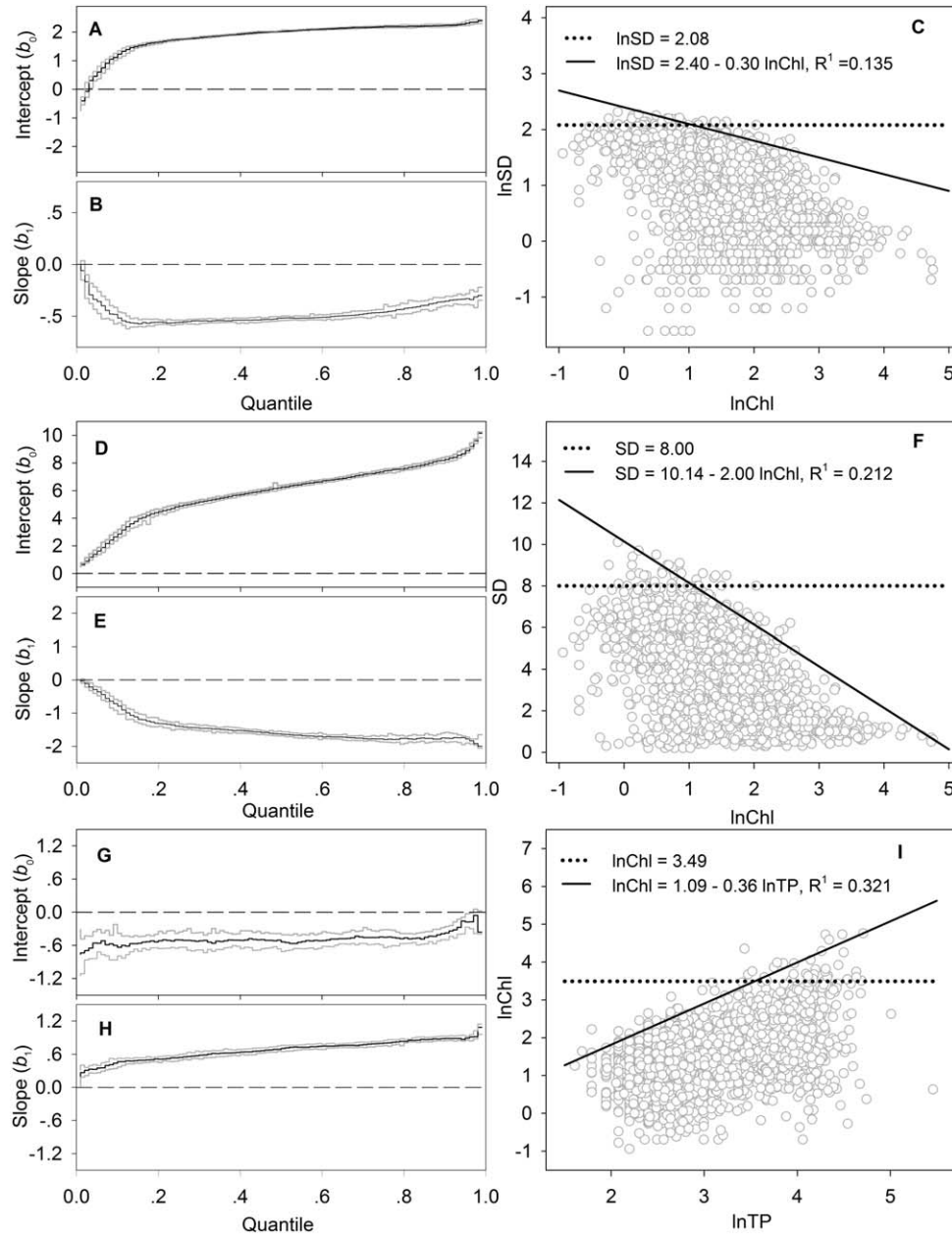
Combining both LC-99th quantile models ( $SD = 10.14 - 2.00\lnChl$  and  $\lnChl = 1.09\lnTP - 0.36$ ) yields  $SD = 10.86 - 2.17\lnTP$ , which was further substituted into the  $TSI_{SD}$  equation to develop the LC-specific  $TSI_{TP}$  equation:

$$TSI_{TP} = 10 \times \left( 6 - \frac{\ln(10.86 - 2.17\lnTP)}{\ln 2} \right)$$

For  $n = 3545$  observations, the  $TSI_{Chl}$  and  $TSI_{TP}$  values generated by the LC-specific equations range from  $24.1$  to  $66.7$  and  $31.2$  to  $68.8$ , respectively, and were significantly lower than those calculated by Carlson (1977)'s equations (paired differences of  $TSI_{Chl}$ : mean =  $-13.2$ , standard deviation =  $4.1$ , 95% confidence interval =  $[-13.4, -13.1]$ ,  $t = -193.4$ ,  $p < 0.01$ , Fig. 4A; paired differences of  $TSI_{TP}$ : mean =  $-7.6$ , standard deviation =  $4.1$ , 95% confidence interval =  $[-7.8, -7.5]$ ,  $t = -110.9$ ,  $p < 0.01$ , Fig. 4B).

#### Classification of trophic states and identification of phosphorus risks

Following Carlson (1977)'s classification of trophic state (Table 1), the LC-specific  $TSI_{Chl}$  value was used to classify all 3545 measurements into three groups: 3434 oligotrophic observations (Group O: 96.9% of the total 3545 observations), 104 mesotrophic observations (Group M: 2.9%) and 8

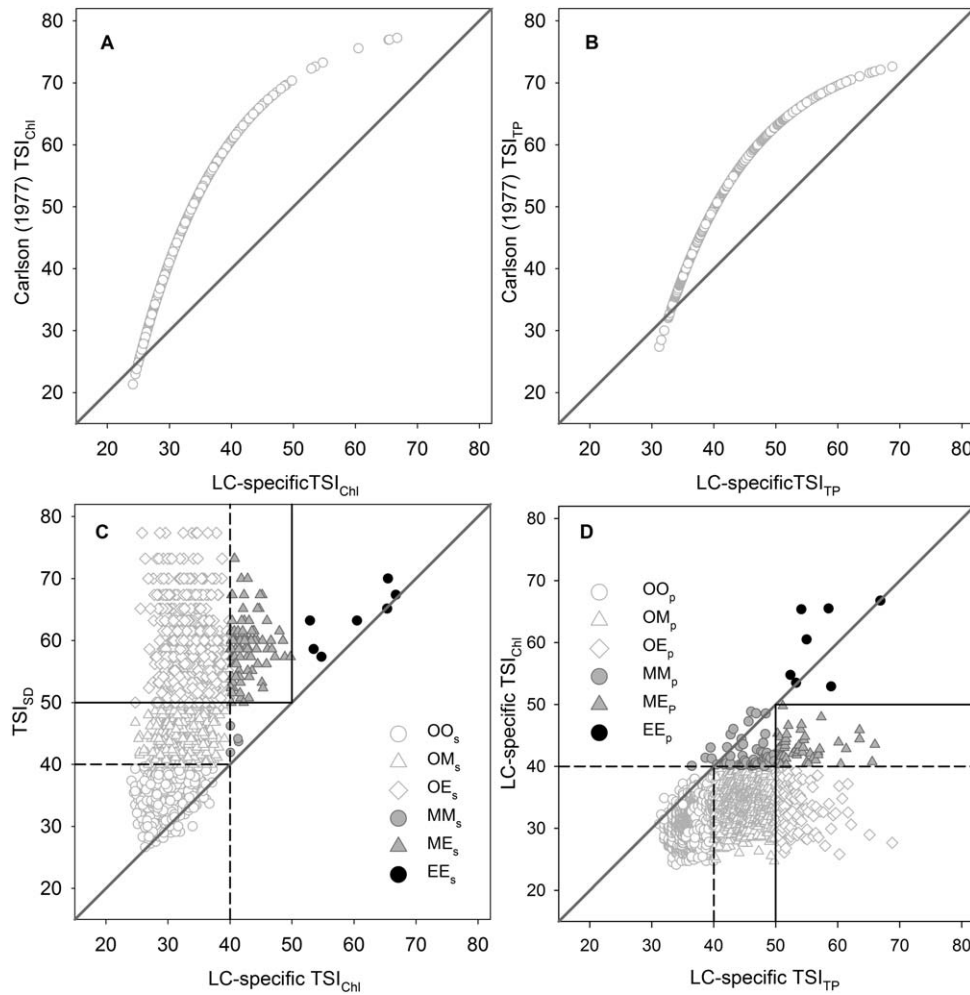


**Fig. 3.** Parameter estimates and 99th quantile fits of  $\ln SD = b_0 + b_1 \ln Chl + \zeta$  (A, B, and C),  $SD = b_0 + b_1 \ln Chl + \zeta$  (D, E, and F) and  $\ln Chl = b_0 + b_1 \ln TP + \zeta$  (G, H, and I). Black lines indicate the parameter estimate (intercept and slope) as step function of quantiles, and gray lines represent the lower and upper bounds (95% confidence interval computed using the “rank” method) of the estimates (A, B, D, E, G, and H). Quantiles range from 0.01 to 0.99 by increments of 0.01 for parameter estimates.

eutrophic observations (Group E: 0.2%).  $TSI_{SD}$  values varied from 26.6 to 83.2, and displayed significantly higher than LC-specific  $TSI_{Chl}$  values (paired differences: mean = 11.2, standard deviation = 8.3, 95% confidence interval = [11.5, 12.1],  $t = 84.5$ ,  $p < 0.01$ , Fig. 4C). As an additional metric, the  $TSI_{SD}$  value was employed to further divide Group O into three types (Type  $OO_s$ ,  $OM_s$ , and  $OE_s$ ) and Group M into two types (Type  $MM_s$  and  $ME_s$ ), respectively (Fig. 4A). Type  $OO_s$  was characterized as oligotrophic in state (45.6%

of Group O observations), while Type  $OM_s$  and Type  $OE_s$  were defined as pseudomesotrophication (30.3%) and pseudoeutrophication (24.1%) in oligotrophic observations. Type  $MM_s$  was identified as mesotrophic state (3.8% of Group M), while Type  $ME_s$  was explained as pseudoeutrophication (96.2%) in mesotrophic observations. Group E (named Type  $EE_s$ ) was characterized as eutrophic in state.

Similarly, LC-specific  $TSI_{TP}$  values were significantly higher than LC-specific  $TSI_{Chl}$  values (paired differences:

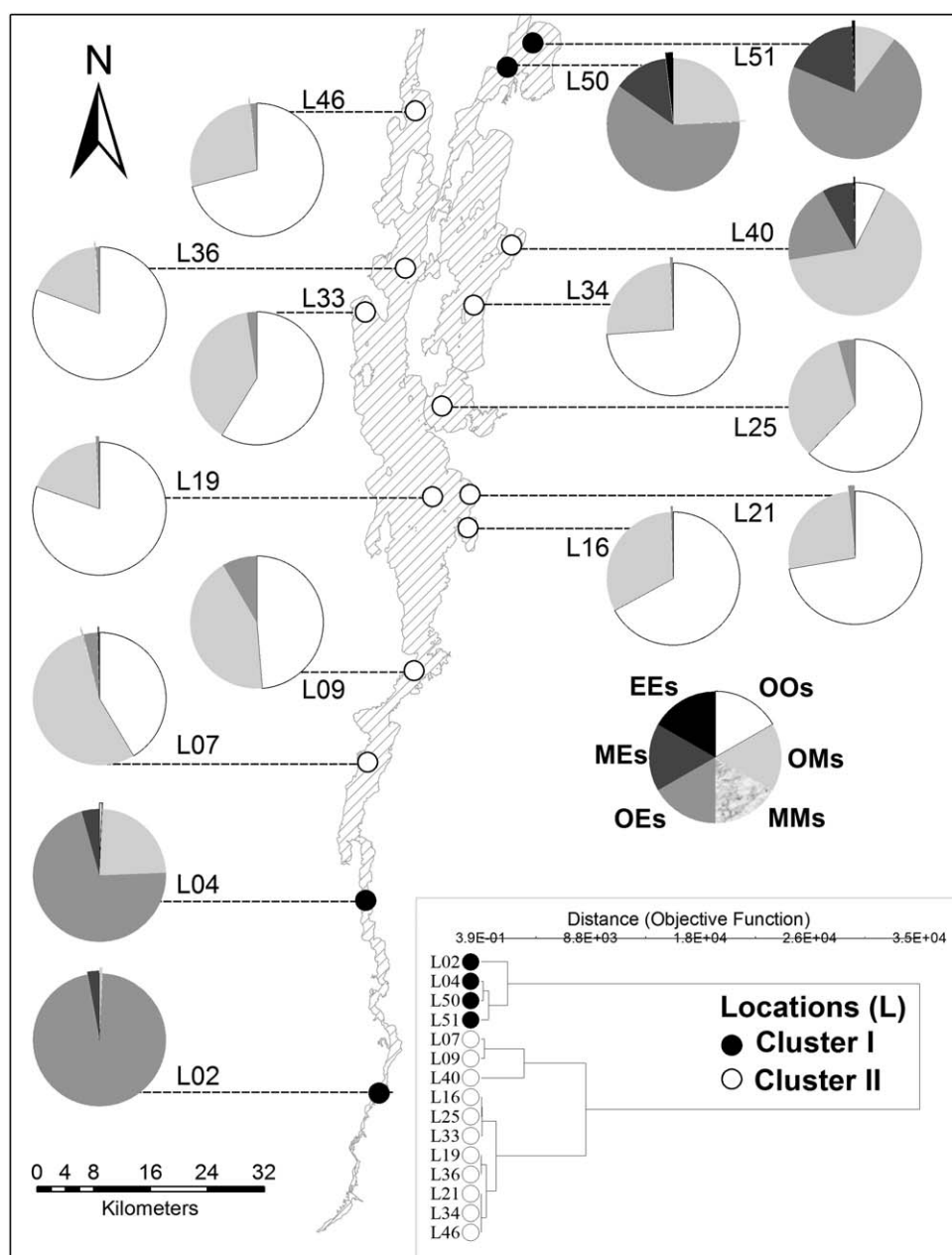


**Fig. 4.** Differences between LC-specific  $TSI_{Chl}$  (A) and  $TSI_{TP}$  (B) and Carlson (1977)'s  $TSI_{Chl}$  and  $TSI_{TP}$ , as well as classification of trophic states (C: Type  $OO_s$ ,  $OM_s$ ,  $OE_s$ ,  $MM_s$ ,  $ME_s$ , and  $EE_s$ ; see Table 2) and identification of phosphorus risk to mesotrophication and eutrophication (D: Type  $OO_p$ ,  $OM_p$ ,  $OE_p$ ,  $MM_p$ ,  $ME_p$ , and  $EE_p$ ; see Table 3). Dark-gray solid line represents the 1 : 1 line (A, B, C, and D). The black short-dashed lines and the black solid lines indicate the threshold value (40) and (50) of trophic state indices ( $TSI_{Chl}/SD/TP$ ), respectively (C and D).

mean = 15.2; standard deviation = 7.5, 95% confidence interval = [14.9, 15.4],  $t = 120.2$ ,  $p < 0.01$ , Fig. 4D). Based on the  $TSI_{TP}$  metric, Group O and Group M were further divided into three types (Type  $OO_p$ ,  $OM_p$ , and  $OE_p$ ) and two types (Type  $MM_p$  and  $ME_p$ ), respectively (Fig. 4B). Type  $OO_p$  was not characterized by excessive phosphorus (67.7% of Group O observations), while Type  $OM_p$  and Type  $OE_p$  could be defined as the risk of excessive phosphorus, which could potentially lead to mesotrophication (27.9%) and eutrophication (4.4%), respectively. Type  $MM_p$  was defined as mesotrophic, which had no risk of excessive phosphorus leading to eutrophication (52.9% of Group M observations); while Type  $ME_p$  was interpreted as the risk of excessive phosphorus, which could potentially lead to eutrophication (47.1% of Group M observations). Group E (also called as Type  $EE_p$ ) has been experiencing eutrophication due to excessive phosphorus loading.

#### Clustering general patterns of Lake Champlain

Based on the frequency at which six trophic types occurred ( $OO_s$ ,  $OM_s$ ,  $OE_s$ ,  $MM_s$ ,  $ME_s$ , and  $EE_s$ ), the HCA analysis grouped the 15 LC-locations into two main clusters (I and II, Fig. 5). Cluster I comprises four monitoring locations distributed in the southern and northeastern portions of the lake (South Lake: L02 and L04; Missisquoi Bay: L50 and L51). The Cluster II locations are distributed in the middle and northwestern portions of the lake: Port Henry Segment (L07); Otter Creek Segment (L09), Shelburne Bay (L16), Main Lake (L19); Burlington Bay (L21); Mallett's Bay (L25); Cumberland Bay (L33); Northeast Arm (L34); Isle LaMotte (L36 and L46), and St. Albans Bay (L40). When the HCA analysis was based on the frequency of phosphorus risks to mesotrophication and eutrophication (Type  $OO_p$ ,  $OM_p$ ,  $OE_p$ ,  $MM_p$ ,  $ME_p$ , and  $EE_p$ ), the 15 LC monitoring locations were partitioned into two main clusters ( $\alpha$  and  $\beta$ , Fig. 6). Cluster  $\alpha$



**Fig. 5.** Spatial patterns and two main clusters (I and II) for the occurrence frequency of trophic states (Type OO<sub>s</sub>, OM<sub>s</sub>, OE<sub>s</sub>, MM<sub>s</sub>, ME<sub>s</sub>, and EE<sub>s</sub>, see Table 2) in LC.

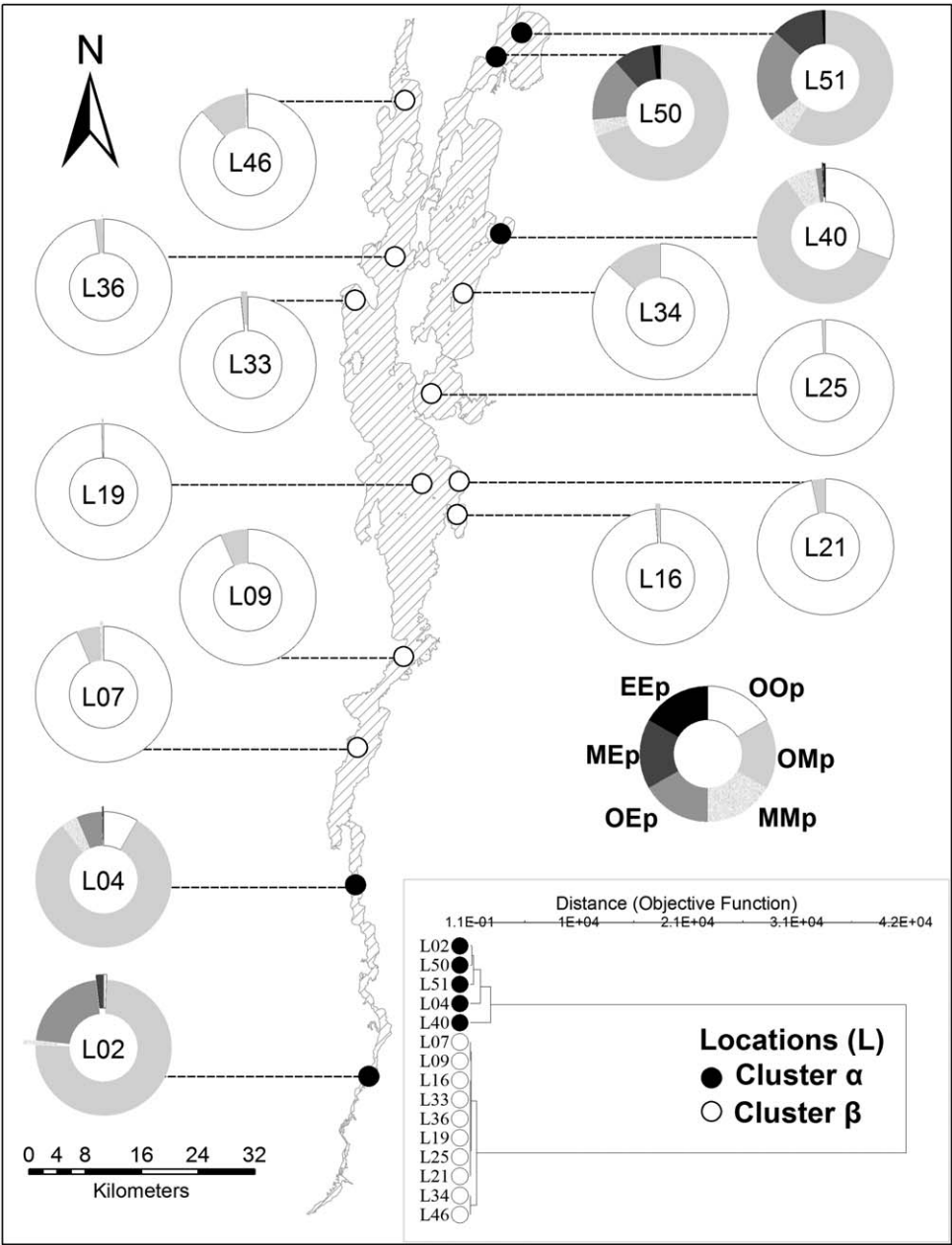
comprised five locations in the southern and northeastern portions of the lake; and the analysis was completely consistent with Cluster I, except for St. Albans Bay (L40) (Fig. 5). Cluster  $\beta$  was formed by 10 locations of Cluster II, involving the middle and northwestern parts of the lake.

### Discussion

It is not entirely surprising that Carlson's 1977 empirical equations for developing TSI<sub>Chl</sub> and TSI<sub>TP</sub> metrics provide

poor model fit to the LC dataset (i.e., Fig. 2), considering the equations were based on water quality data compiled from select lake ecosystems such as Crater Lake and Lake Superior (Lawson 1972; Schelske et al. 1972) and not necessarily intended by the author to represent a broad spectrum of lake environments worldwide. However, these empirical equations have been treated as such by many in the limnological community who applied Carlson (1977)'s TSI<sub>Chl/TP</sub> equations directly to their lake systems (e.g., Ludovisi and Poletti 2003; Westover et al. 2009; Wang et al. 2013). In





**Fig. 6.** Spatial assessment of phosphorus risks to mesotrophication and eutrophication (Type OO<sub>p</sub>, OM<sub>p</sub>, OE<sub>p</sub>, MM<sub>p</sub>, ME<sub>p</sub>, and EE<sub>p</sub>; see Table 3) and two main clusters (α and β) of the 15 sampling locations in LC.

contrast, our work suggests a relatively robust statistical approach to developing ecosystem-specific metrics of eutrophication assessment for other lakes where the size of the existing SD, Chl, and TP water quality data is similar to (or larger than) that of LC.

**Revised TSI<sub>Chl</sub> and TSI<sub>TP</sub> metric**

Given the low coefficient of determination in the LC-summer lnSD =  $f(\ln\text{Chl})$  relationship (Fig. 2A), we determined that water clarity for most of the LC-summer observa-

tions is, to a large extent, driven by nonalgal turbidity rather than algal biomass. Thus, it is not appropriate to use the LC-summer lnSD =  $f(\ln\text{Chl})$  relationship to produce an ecologically meaningful TSI<sub>Chl</sub> metric for LC, as the metric is strongly influenced and often driven by nonalgal turbidity rather than algal biomass. QR has a sound theoretical basis for this application because it can reasonably characterize the heterogeneity in response that may arise from the impact of these kinds of “unmeasured factors” when deriving empirical relationships. This is further manifested for SD

$= 10.14 - 2.00 \ln \text{Chl}$ , which provides a better fit of the upper boundary (99th quantile) than  $\ln \text{SD} = 2.40 - 0.30 \ln \text{Chl}$ ; and it supports the development of a metric that is inherently representative of algal-based trophic state in LC. The powerful effect of QR on the generation of the  $\text{TSI}_{\text{Chl}}$  metric is illustrated by the dramatic systematic offset of  $\text{TSI}_{\text{Chl}}$  from the 1 : 1 line (Fig. 4A). In this instance, it appears that using Carlson (1977)'s approach on the LC data produces an unwarranted systematic overestimate of trophic concern due to high levels of nonalgal turbidity. This overestimate is consistent with the high watershed to lake area ratio of 19 : 1, which produces large pulses of riverine suspended sediment and potentially riverine dissolved organic carbon, both of which would produce nonalgal light attenuation (Smeltzer et al. 2012). As such, the LC-specific QR-derived  $\text{TSI}_{\text{Chl}}$  metric should provide a better tool than Carlson (1977)'s metric for assessing and monitoring the trophic status of this particular ecosystem. We must emphasize that specific 99th quantile equations and  $\text{TSI}_{\text{Chl}}$  metrics derived in this work are only appropriate for LC and cannot be directly used beyond the lake. However, our QR-based framework for generating a lake-specific  $\text{TSI}_{\text{Chl}}$  metric (as outlined in Fig. 1B) is applicable to other lakes with the existing water quality data.

In light of our successful modification of the  $\text{TSI}_{\text{Chl}}$  metric, we turned our attention to a similar framework for the revision of the  $\text{TSI}_{\text{TP}}$  metric. The low coefficient of determination observed in the LC-summer  $\ln \text{Chl} = f(\ln \text{TP})$  relationship (Fig. 2B) suggests that other unmeasured factors, rather than phosphorus, influence algal biomass for most of the LC-summer observations. Similar to the parameter estimates of the  $\text{SD} = f(\ln \text{Chl})$  relationships, the coefficient of determination for  $\ln \text{Chl} = 1.09 \ln \text{TP} - 0.36$  confirms that QR (99th) has generated the upper boundary where TP is driving algal biomass of LC (Fig. 3I). Since the LC-99th model of  $\ln \text{Chl} = f(\ln \text{TP})$  indicates phosphorus limitation of phytoplankton biomass, it should be used to derive a LC-specific  $\text{TSI}_{\text{TP}}$  metric that is potentially useful for assessment and management of this lake. The dramatic effect of different approaches for generating the  $\text{TSI}_{\text{TP}}$  metrics is evident in the significant overestimation of  $\text{TSI}_{\text{TP}}$  produced using Carlson (1977)'s empirical equation compared to the LC-specific  $\text{TSI}_{\text{TP}}$  equation (Fig. 4B). The observed difference is nontrivial and important for developing an ecosystem-specific  $\text{TSI}_{\text{TP}}$  metric relevant to a particular lake ecosystem and useful for monitoring ecosystem dynamics over space and time. Again, we would not recommend the direct application of the LC-specific  $\text{TSI}_{\text{TP}}$  equation beyond LC; but our QR-based framework (outlined in Fig. 1B) offers a powerful alternative and more robust approach for creating  $\text{TSI}_{\text{TP}}$  equations for any specific lake using the existing SD, Chl, and TP water quality data.

#### TSI metric deviation and establishment of dual metrics

In LC, the  $\text{TSI}_{\text{Chl}}$  values were significantly lower than  $\text{TSI}_{\text{SD}}$  values (Fig. 4C), suggesting nonalgal turbidity plays an

important role in light attenuation (Carlson and Havens 2005; Xu et al. 2010). However, application of the original  $\text{TSI}_{\text{Chl}}$  equation in LC is partially flawed, because the empirical data used to derive this equation are not useful indicators of algal biomass for this system (Fig. 2A). Since the QR-derived  $\text{TSI}_{\text{Chl}}$  was generated from data where water clarity is driven by algal biomass (Fig. 3F), our modified ecosystem-specific metrics are more useful and accurate when assessing and monitoring nonalgal turbidity in this lake ecosystem relative to previous approaches (e.g., Carlson and Havens 2005; Xu et al. 2010). Furthermore, utilization of the  $\text{TSI}_{\text{Chl/SD}}$  deviations to develop a LC-specific dual metric for classifying the pseudoeutrophic state of oligotrophic and mesotrophic observations and the pseudomesotrophic state of oligotrophic observations is a potentially powerful tool for research and management communities. As an addition to Carlson (1977)'s single metric trophic-state classification (oligotrophic, mesotrophic, and eutrophic), the new dual-metric classification of pseudotrophic states (OMs, OEs, and MEs) may be used to identify water bodies that are particularly susceptible to trophic shift due to disturbances from nonalgal particulate matter and algal biomass.

Similar to the observed deviation of  $\text{TSI}_{\text{SD}}$  from  $\text{TSI}_{\text{Chl}}$  for LC, we found that  $\text{TSI}_{\text{TP}}$  had systematically higher values than the corresponding  $\text{TSI}_{\text{Chl}}$  (Fig. 4B). This is not particularly surprising, as in practice, exclusive phosphorus limitation is not always easily demonstrated across time and space in many water bodies, and the deviation of  $\text{TSI}_{\text{TP}}$  from  $\text{TSI}_{\text{Chl}}$  has often been detected when using Carlson (1977)'s empirical equations with new datasets (An and Park 2003; James et al. 2009; Xu et al. 2010). Carlson and Havens (2005) used the deviation of  $\text{TSI}_{\text{TP}}$  from  $\text{TSI}_{\text{Chl}}$  to infer that other factors (e.g., zooplankton grazing) reduce algal biomass below levels predicated from TP in a phosphorus-limited system. However, the poor correlation between TP and Chl (Fig. 2B) again suggests that studying the deviation of TSI metrics derived from the poorly correlated empirical relationship is not ideal for assessing or monitoring the LC ecosystem. Since the LC-specific  $\text{TSI}_{\text{TP}}$  equation generated by the QR-derived  $\ln \text{Chl} = f(\ln \text{TP})$  is more representative of the phosphorus limitation of algal biomass in LC (Fig. 2D), it should provide better prediction of potential trophic state for a given TP concentration than the original  $\text{TSI}_{\text{TP}}$  equation. Therefore,  $\text{TSI}_{\text{Chl/TP}}$  deviations are more meaningful in the context of trophic status assessment and phosphorus loading threats for LC, as well as detection and analysis of situations when factors other than phosphorus limitation or loading are driving algal biomass across the LC ecosystem. Furthermore, the deviation of  $\text{TSI}_{\text{TP}}$  from  $\text{TSI}_{\text{Chl}}$  can be harnessed as another useful dual metric for identifying ecosystems that contain excessive phosphorus, which could sustain a higher algal-based trophic state than that observed when phosphorus becomes the limiting factor. For example, the deviation of  $\text{TSI}_{\text{TP}}$  from  $\text{TSI}_{\text{Chl}}$  in oligotrophic waters and mesotrophic

waters indicates that excessive phosphorus could drive future eutrophication of those waters if there is a shift in the dynamics that limit algal productivity (e.g., hydrodynamics, nitrogen loading, climate change, zooplankton etc.). This newly developed dual metric space could therefore generate critical information for lake research and management communities to co-ordinate and focus future efforts in lakes and their contributing watersheds.

### Clustering patterns of Lake Champlain ecosystem

When applying our QR-derived  $TSI_{CHL/TP}$  equations and the related dual metric-driven classification schemes to LC-specific water quality dataset, dramatic variability in the spatial distribution of trophic status (Fig. 5) and excessive phosphorous risk (Fig. 6) was observed. Eutrophication has not been detected for the middle and northwestern areas of the lake, where oligotrophic states were still dominant ( $OO_s$ , Fig. 5) and excessive phosphorus potentially leads to mesotrophication ( $OM_p$ , Fig. 6). Low frequency of eutrophication ( $EE_s$ ) occurred at the southern and northeastern portions of LC, which were dominated by pseudoeutrophication ( $OE_s$  and  $ME_s$ , Fig. 5) but characterized as high risk of excessive phosphorus leading to eutrophication ( $OE_p$  and  $ME_p$ , Fig. 6). These results suggest that the whole lake could be divided into two main areas based on TSI metrics and related classification. In this case study, the general dual-metric patterns within the LC ecosystem may be used to identify relatively pristine and threatened portions of the lake; and this analysis is a particularly robust example due to the hydrodynamic and ecological diversity of the 15 monitoring stations used for this study. In the relatively deep and well-circulated middle and northwestern portions of the lake, we did not detect eutrophication, pseudoeutrophication and excessive phosphorus risk to eutrophication, indicating that these regions remain relatively pristine and immediate threats associated with a trophic shift due to phosphorus loading are relatively low. Conversely, the relatively shallow and agricultural watershed-dominated southern and northeastern regions of the lake were classified as eutrophic or pseudoeutrophic ecosystems with excessive phosphorus risk for eutrophication. Therefore, our metrics identify these lake segments of LC as areas of trophic concern that warrant additional research and management resources to better understand ecosystem processes and the implementation of nutrient control measures. Furthermore, considering the diverse hydrodynamic and biological environments associated with the lake segments studied here, coupled with the general confirmation of existing knowledge developed from long-term monitoring and extensive LC ecosystem research (i.e., LCBP 2012), the approach outlined here should be broadly applicable to a diverse array of lake environments and ecosystems. As such, this relatively simple but robust lake-specific approach can be employed by relevant management and research communities to monitor and characterize diverse lake ecosystems and assess the threat potential for ecosystem shifts.

### References

- An, K. G., and S. S. Park. 2002. Indirect influence of the summer monsoon on chlorophyll-total phosphorus models in reservoirs: A case study. *Ecol. Model.* **152**: 191–203. doi:10.1016/S0304-3800(02)00020-0
- An, K. G., and S. S. Park. 2003. Influence of seasonal monsoon on the trophic state deviation in an Asian Reservoir. *Water Air Soil Pollut.* **145**: 267–287. doi:10.1023/A:1023688819724
- Brown, C. D., M. V. Hoyer, R. W. Bachmann, and D. E. Canfield. 2000. Nutrient–chlorophyll relationships: An evaluation of empirical nutrient–chlorophyll models using Florida and north-temperate lake data. *Can. J. Fish. Aquat. Sci.* **57**: 1574–1583. doi:10.1139/f00-090
- Cade, B. S., and Q. Guo. 2000. Estimating effects of constraints on plant performance with regression quantiles. *Oikos* **91**: 245–254. doi:10.1034/j.1600-0706.2000.910205.x
- Cade, B. S., and B. R. Noon. 2003. A gentle introduction to quantile regression for ecologists. *Front. Ecol. Environ.* **1**: 412–420. doi:10.1890/1540-9295(2003)001[0412:AGITQR]2.0.CO;2
- Cade, B. S., B. R. Noon, and C. H. Flather. 2005. Quantile regression reveals hidden bias and uncertainty in habitat models. *Ecology* **86**: 786–800. doi:10.1890/04-0785
- Cade, B. S., J. W. Terrell, and R. L. Schroeder. 1999. Estimating effects of limiting factors with regression quantiles. *Ecology* **80**: 311–323. doi:10.1890/0012-9658(1999)080[0311:EEOLFW]2.0.CO;2
- Carlson, R. E. 1977. A trophic state index for lakes. *Limnol. Oceanogr.* **22**: 361–369. doi:10.4319/lo.1977.22.2.0361
- Carlson, R. E., and K. E. Havens. 2005. Simple graphical methods for the interpretation of relationships between trophic state variables. *Lake Reservoir Manage.* **21**: 107–118. doi:10.1080/07438140509354418
- Carvalho, L., and others. 2013. Sustaining recreational quality of European lakes: Minimizing the health risks from algal blooms through phosphorus control. *J. Appl. Ecol.* **50**: 315–323. doi:10.1111/1365-2664.12059
- Dodds, W. K., and others. 2009. Eutrophication of U.S. freshwaters: Analysis of potential economic damages. *Environ. Sci. Technol.* **43**: 12–19. doi:10.1021/es801217q
- Facey, D. E., J. E. Marsden, T. B. Mihuc, and E. A. Howe. 2012. Lake Champlain 2010: A summary of recent research and monitoring initiatives. *J. Great Lakes Res.* **38**: 1–5. doi:10.1016/j.jglr.2011.12.001
- Hoyer, M. V., T. K. Frazer, S. K. Notestein, and D. E. Canfield, Jr. 2002. Nutrient, chlorophyll, and water clarity relationships in Florida's nearshore coastal waters with comparisons to freshwater lakes. *Can. J. Fish. Aquat. Sci.* **59**: 1024–1031. doi:10.1139/f02-077
- Huszar, V. L. M., N. F. Caraco, F. Roland, and J. Cole. 2006. Nutrient-chlorophyll relationships in tropical subtropical lakes: Do temperate models fit? *Biogeochemistry* **79**: 239–250. doi:10.1007/s10533-006-9007-9

- James, R., K. Havens, G. Zhu, and B. Qin. 2009. Comparative analysis of nutrients, chlorophyll and transparency in two large shallow lakes (Lake Taihu, P.R. China and Lake Okeechobee, USA). *Hydrobiologia* **627**: 211–231. doi:10.1007/s10750-009-9729-5
- Jones, J. R., and J. A. Hubbart. 2011. Empirical estimation of non-chlorophyll light attenuation in Missouri reservoirs using deviation from the maximum observed value in the secchi-chlorophyll relationship. *Lake Reservoir Manage* **27**: 1–5. doi:10.1080/07438141.2011.554962
- Jones, J. R., D. V. Obrecht, and A. P. Thorpe. 2011. Chlorophyll maxima and chlorophyll: Total phosphorus ratios in Missouri reservoirs. *Lake Reservoir Manage*. **27**: 321–328. doi:10.1080/07438141.2011.627625
- Koenker, R., and J. A. Machado. 1999. Goodness of fit and related inference processes for quantile regression. *J. Am. Stat. Assoc.* **94**: 1296–1310. doi:10.1080/01621459.1999.10473882
- Koenker, R., S. Portnoy, T. Tian Ng, A. Zeileis, P. Grosjean, and B. D. Ripley. 2013. quantreg: Quantile Regression and related models. R package version 5.05. Available from <http://CRAN.R-project.org/package=quantreg>
- LAKE CHAMPLAIN BASIN PROGRAM (LCBP). 2012. State of the lake and ecosystems indicators report. Grand Isle, Vermont. Available from <http://sol.lcbp.org/scorecard.html>
- Lawson, D. W. 1972. Temperature, transparency, and phytoplankton productivity in Crater Lake, Oregon. *Limnol. Oceanogr.* **17**: 410–417. doi:10.4319/lo.1972.17.3.0410
- Levine, S. N., and others. 2012. The eutrophication of Lake Champlain's northeastern arm: Insights from paleolimnological analyses. *J. Great Lakes Res.* **38**: 35–48. doi:10.1016/j.jglr.2011.07.007
- Lind, O. T. 1986. The effect of non-algal turbidity on the relationship of secchi depth to chlorophyll *a*. *Hydrobiologia* **140**: 27–35. doi:10.1007/BF00006726
- Ludovisi, A., and A. Poletti. 2003. Use of thermodynamic indices as ecological indicators of the development state of lake ecosystems. 1. Entropy production indices. *Ecol. Model.* **159**: 203–222. doi:10.1016/S0304-3800(02)00277-6
- Matthew, F. K., and J. R. Jones. 2006. Temporal variation and assessment of trophic state indicators in Missouri Reservoir: Implication for lake monitoring and management. *Lake Reservoir Manage.* **22**: 261–271. doi:10.1080/07438140609353904
- Mazumder, A., and K. E. Havens. 1998. Nutrient-chlorophyll-secchi relationships under contrasting grazer communities of temperate versus subtropical lakes. *Can. J. Fish. Aquat. Sci.* **55**: 1652–1662. doi:10.1139/cjfas-55-7-1652
- McCune, B., and M. Mefford. 1999. PC-ORD multivariate analysis of ecological data, Version 4, Oregon, USA.
- Mooij, W. M., and others. 2010. Challenges and opportunities for integrating lake ecosystem modelling approaches. *Aquat. Ecol.* **44**: 633–667. doi:10.1007/s10452-010-9339-3
- R Development Core Team. 2014. A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from <http://www.R-project.org>
- Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker. 2001. Catastrophic shifts in ecosystems. *Nature* **413**: 591–596. doi:10.1038/35098000
- Schelske, C. L., L. E. Veldt, M. A. Santiago, and E. F. Stoermer. 1972. Nutrient enrichment and its effect on phytoplankton production and species composition in Lake Superior, p. 149–165. *Proceedings of the 15th Conference on Great Lakes Research*, Ohio, USA.
- Schindler, D. W. 2012. The dilemma of controlling cultural eutrophication of lakes. *Proc. R. Soc. B Biol. Sci.* **279**: 4322–4333. doi:10.1098/rspb.2012.1032
- Smeltzer, E., A. D. Shambaugh, and P. Stangel. 2012. Environmental change in Lake Champlain revealed by long-term monitoring. *J. Great Lakes Res.* **38**: 6–18. doi:10.1016/j.jglr.2012.01.002
- Smith, V. H., and D. W. Schindler. 2009. Eutrophication science: Where do we go from here. *Trends Ecol. Evol.* **24**: 201–207. doi:10.1016/j.tree.2008.11.009
- Soranno, P. A., K. S. Cheruvilil, R. J. Stevenson, S. L. Rollins, S. W. Holden, S. Heaton, and E. Torng. 2008. A framework for developing ecosystem-specific nutrient criteria: Integrating biological thresholds with predictive modeling. *Limnol. Oceanogr.* **53**: 773–787. doi:10.4319/lo.2008.53.2.0773
- Stow, C. A., and Y. Cha. 2013. Are chlorophyll *a*-total phosphorus correlations useful for inference and prediction? *Environ. Sci. Technol.* **47**: 3768–3773. doi:10.1021/es304997p
- Sulis, A., P. Buscarinu, and G. M. Sechi. 2011. Using reservoir trophic-state indexes in optimisation modelling of water-resource systems. *Environ. Model. Softw.* **26**: 731–738. doi:10.1016/j.envsoft.2011.01.001
- Swift, T. J., J. Perez-Losada, S. G. Schladow, J. E. Reuter, A. D. Jassby, and C. R. Goldman. 2006. Water clarity modeling in Lake Tahoe: Linking suspended matter characteristics to secchi depth. *Aquat. Sci.* **68**: 1–15. doi:10.1007/s00027-005-0798-x
- Umbanhowar, C. E., Jr., P. Camill, and J. Dorale. 2011. Regional heterogeneity and the effects of land use and climate on 20 lakes in the big woods region of Minnesota. *J. Paleolimnol.* **45**: 151–166. doi:10.1007/s10933-010-9486-5
- Vermont Department of Environmental Conservation (VTDEC), and New York State Department of Environmental Conservation (NYDEC). 2013. Long-term water quality and biological monitoring project for Lake Champlain-Quality Assurance Project Plan. Grand Isle, Vermont. Available from [http://www.watershedmanagement.vt.gov/lakes/htm/lp\\_longterm.htm](http://www.watershedmanagement.vt.gov/lakes/htm/lp_longterm.htm)
- Wagner, T., P. A. Soranno, K. E. Webster, and K. S. Cheruvilil. 2011. Landscape drivers of regional variation in the relationship between total phosphorus and chlorophyll in lakes. *Freshw. Biol.* **56**: 1811–1824. doi:10.1111/j.1365-2427.2011.02621.x



- Wang, L., L. Liu, and B. Zheng. 2013. Eutrophication development and its key regulating factors in a water-supply reservoir in North China. *J. Environ. Sci.* **25**: 962–970. doi:[10.1016/S1001-0742\(12\)60120-X](https://doi.org/10.1016/S1001-0742(12)60120-X)
- Westover, K. S., K. A. Moser, D. F. Porinchu, G. M. MacDonald, and X. W. Wang. 2009. Physical and chemical limnology of a 61-lake transect across mainland Nunavut and southeastern Victoria Island, Central Canadian Arctic. *Fundam. Appl. Limnol.* **175**: 93–112. doi:[10.1127/1863-9135/2009/0175-0093](https://doi.org/10.1127/1863-9135/2009/0175-0093)
- Xu, Y., Q. Cai, X. Han, M. Shao, and R. Liu. 2010. Factors regulating trophic status in a large subtropical reservoir, China. *Environ. Monit. Assess.* **169**: 237–248. doi:[10.1007/s10661-009-1165-5](https://doi.org/10.1007/s10661-009-1165-5)
- Xu, Y., M. Shao, X. Han, and Q. Cai. 2011. Temporal asynchrony of trophic status between mainstream and tributary bay within a giant dendritic reservoir: The role of local-scale regulators. *Water Air Soil Pollut.* **219**: 271–284. doi:[10.1007/s11270-010-0705-5](https://doi.org/10.1007/s11270-010-0705-5)

## Acknowledgments

We are grateful to the staff of the Vermont Department of Environmental Conservation and New York State Department of Environmental Conservation, who collected and processed data for a long-term monitoring program (LTMP 1992–2012) on Lake Champlain. We appreciate Dr. Brian Cade, another anonymous reviewer and associate editor (Prof. John Smol) for their constructive comments in improving this manuscript, and Prof. Roger Koenker for assistance with quantile regression. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. Support provided by Vermont EPSCoR with funds from the National Science Foundation Grant EPS-110131.

*Submitted 29 September 2014*

*Revised 5 February 2015*

*Accepted 14 February 2015*

*Associate editor: Prof. John Smol*