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Temporal Variation and Assessment of Trophic State Indicators in Missouri Reservoirs: Implication for Lake Monitoring and Management

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Abstract

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The magnitude and management implications of temporal variability in trophic state metrics was simulated by measuring mean values of total phosphorus (TP), total nitrogen (TN), chlorophyll (Chl) and Secchi depth (SD) in summer (May-August) and detecting trends in these variables in a virtual lake undergoing gradual (doubling over 20 years) and abrupt (doubling over two years) change. Numbers of samples required (samples per summer over number of summers) to adequately detect these rates of change were used to show the size and management implications of temporal variability. Long-term data from 116 Missouri reservoirs, including eight summer data sets based on daily sampling, provided estimates of autocorrelation and variation within and among summers (seasonal and year-to-year variance) used in Monte Carlo simulations to evaluate sampling requirements. In simulations based on median variance, obtaining long-term means with 95% confidence intervals spanning less than a factor of two took from three years (TN) to eight years (Chl) with monthly samples (n=3 per summer). For a lake with mean values doubling every 20 years, linear regression had >75% chance of detecting the trend after 13 years of monthly samples for TN, but Chl required >20 years. For a lake with Chl doubling over two years, at least six years of pre-change data and 11 years of post-change data were required before monthly sampling gave >75% probability of detecting the trend. Increasing sampling to weekly frequency (n=16 per summer) in most scenarios reduced required duration of sampling by <2 years. Variability data from lakes in other regions fall in the range exhibited by Missouri reservoirs. Results emphasize the need for long-term data to fulfill lake management needs and suggest that ordinary lake monitoring typically will not detect trends in individual lakes.

Key Words: temporal variation, reservoirs, trend detection, trophic state, sampling requirements

The central focus of lake assessment is to determine the current trophic state of a study lake and detect whether conditions are changing over time. Lake monitoring for these purposes is conducted against a backdrop of temporal variation (Knowlton *et al.* 1984, Knowlton and Jones 1995). Unraveling mechanisms underlying the wax and wane of algal populations, flux of nutrients, changes in transparency and other lake features have long been studied as a thrust of basic aquatic ecology (Reynolds 1997). This body of information suggests lakes are constantly changing over time; conditions vary in the short-term measured in hours or days and in the longer-term measured in seasonal shifts or year-to-year fluctuations in response to weather or other naturally stochastic processes (Harris 1980). Thus, knowing whether trophic state metrics in a particular lake are changing over time requires distinction between fluctuations caused by "ordinary" temporal variability and directional changes resulting from human intervention (intentional or not).

Ordinary temporal variability is familiar to any lake observer; all parties recognize recurring seasonal patterns and short-term responses to storms. Less familiar are the statistical features of temporal variability needed to invoke or interpret lake management practices. The literature on temporal variability is mathematical and somewhat abstract (Knowlton *et al.* 1984, Marshall *et al.* 1988, Smeltzer *et al.* 1989, France and Peters 1992, Larsen *et al.* 1995, 2001, Terrell *et al.* 2000). As such, temporal variability is not commonly considered in lake assessments and there is a danger of lake practitioners being under-informed about the magnitude of ordinary fluctuations in water quality variables and how temporal variation might interfere with answers to basic lake management questions.

Increased knowledge of "ordinary" temporal variation is important in the United States as we enter a new era in lake management based on development and implementation of federally mandated nutrient criteria (Gibson *et al.* 2000, Knowlton and Jones 2006). Questions about ordinary variability should be addressed when applying numeric standards. For example, can compliance with a nutrient standard be evaluated using measurements from a single year, or are several years of data needed to "average out" ordinary variability. The conundrum stems from the fact that nutrient standards are static while lakes are dynamic. Awareness of the extent of lake dynamics should be integral to all aspects of lake management, including interpretation of nutrient criteria.

One way to raise awareness of temporal variability is to illustrate its magnitude within the context of lake management. In temporally variable systems multiple samples are needed to determine average conditions and changes in individual lakes, and estimating the number of samples required to answer such questions provides a practical illustration of temporal variability. This study illustrates some key quantitative features of temporal variation and assessment of trophic state by addressing these questions using several scenarios designed around simulations of a typically variable lake. Variability data from Missouri reservoirs were used to calibrate the answers, but these data encompass a range that includes lakes in other regions.

The first hypothetical scenario involves estimating trophic state in terms of average total phosphorus (TP), total nitrogen (TN), chlorophyll (Chl) or Secchi depth (SD) for a lake not undergoing any long-term change. The second and third scenarios involve detecting a change in these variables in a lake that is gradually changing (by two-fold over 20 years) or abruptly changing (two-fold over two years). Confidence intervals of 95% were used as the measure of how well trophic state has been estimated (first scenario), and simple regression was used as the method of detecting change over time in the second and third scenarios. These specific procedures were used not because they are necessarily the optimal statistical techniques for answering such questions, but because they are universally familiar. To evaluate these scenarios a "Monte Carlo" approach was used wherein a data series was created simulating 20 consecutive summer sampling periods from a Missouri reservoir that matches the major statistical features of real lake data. The imitated statistical features included the amount of variability within and among summers and autocorrelation between measurements taken close together in time. The simulated sampling of these time series were at rates of 3, 6 or 16 times per summer (roughly monthly, semi-monthly and weekly) over periods of 2-20 years to generate annual averages that were used to construct confidence intervals or perform regression analysis. Each sampling scenario was repeated with 1000 simulated data sets to evaluate typical performance.

Statistical formulations used are a form of power analysis (Thomas 1997, Urquhart *et al.* 1998) and are sound for the simplified scenarios considered. The intention is not, however, to provide a rigorous formula for design of sampling schemes or to prescribe how best to detect temporal trends in lakes. The only goal is to raise awareness of temporal variability as an important characteristic of lakes with clear implications for management. The estimates of "how many samples" developed from these scenarios are a means to that end.

Data and Analysis

Simulations

Simulation data sets consisted of series of "observed values" (OVs) for a simulated parameter representing daily measurements for 20 consecutive "summers" of 108 days (16 May-31 August). OVs were generated from "annual expected values" (AEVs) representing conditions specific to that year, which in turn were generated from "long-term expected values" (LEVs). LEVs represent the trend (or lack thereof) in the data during the 20 year series. In simulating a lake undergoing change, LEVs were a function of the sampling date. In the "gradual change" scenario, LEVs increased at a constant (arithmetic) rate over the 20 years, while in the "abrupt change" scenario, LEVs were constant before and after a two-year period of rapid increase. In both scenarios, LEVs doubled during the sequence (Fig. 1a). In the third (no-change) scenario, LEVs remained constant.

AEVs paralleled LEVs but were offset by an amount chosen randomly to represent year-to-year variation around the overall trend (Fig. 1a). The amount of offset was chosen for each year in the 20-year series from a random normal distribution with mean zero and a standard deviation of V_y (Fig. 1b). OVs were calculated as an autocorrelated time series. OVs consisted of the AEV for a given date plus or minus a residual (r_i). The first residual in each summer series (r_1, representing the observation for 16 May) was determined randomly from a normal distribution with mean of zero and a standard deviation = V_s. Each subsequent residual was calculated by multiplying an autocorrelation coefficient, "ρ", times the previous residual and adding an error term drawn from a random normal deviate with mean zero and standard deviation =V_e (Fig. 1b).

"Sampling" from simulated data sets was done at three levels roughly representing monthly, semi-monthly and weekly samples (n=3, 6, and 16 per summer, respectively). Weekly samples consisted of every seventh OV in each series (days 1, 8, 15, etc.). Monthly and semi-monthly samples were taken at fixed intervals of 31 and 16 days, respectively, with the starting date picked randomly from among the first 44 (n=3) or 28 (n=6) days of each summer series.

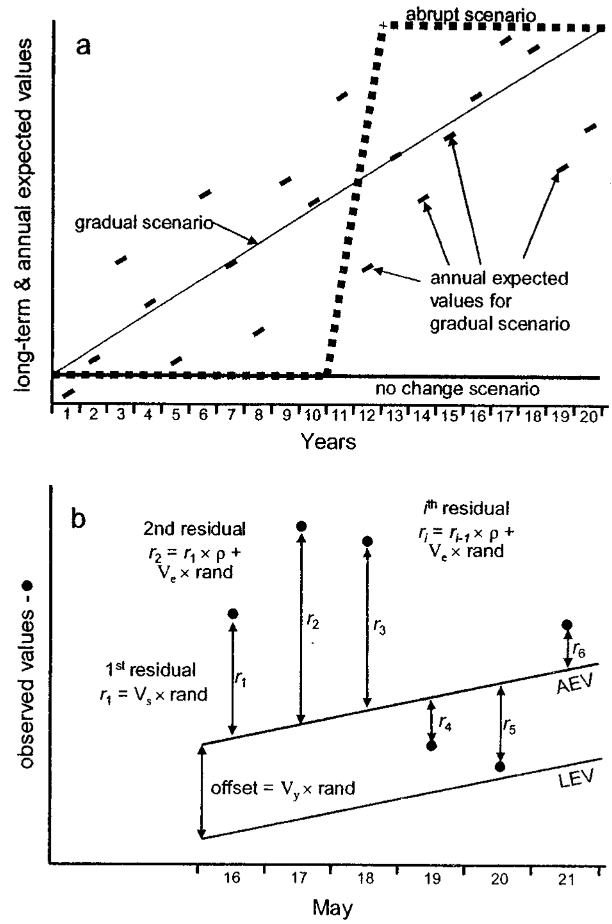

Figure 1.-Simulation features. (a) Long-term expected values (LEV's) for no-change, gradual and abrupt scenarios and annual expected values (AEV's) for gradual scenario. (b). Example of estimation of observed values (OV's) in summer time series. Values of "rand" are random numbers drawn from a normal population with a mean of zero and standard deviation of 1 (RANNOR function in SAS 8.02). Residuals and variance components are described in the text.

Calibration

Performance of simulations depends on values of V_y, V_s, V_e and ρ. Values of these parameters were selected to match the median variance characteristics of data from an annual Missouri-wide lake assessment program conducted during 1989-2003 in which measurements of TP, TN, Chl and SD were collected from 134 Missouri reservoirs. Sampling began in mid-May and ended in late-August each year and included 3-4 samples per water body. Initially the total data set comprised 1265 lake-years of data with at least four years of data per reservoir. Individual reservoir data sets were screened to eliminate those with possible long-term trends. Two reservoirs were excluded because of changes in pelagic conditions related to macrophyte control measures. Sixteen waterbodies were excluded because regression showed significant ($p<0.01$) temporal trends among seasonal means of one or more variables. The final data set consisted of 1085 lake-years of data from 116 reservoirs. Samples were collected from the surface layer at a location near the dam in all cases. SD was measured with a 20-cm black and white disk. Water samples were analyzed for TP (Prepas and Rigler 1982) and TN (Crumpton *et al.* 1992), and Chl (Pall A-E glass fiber filters; Sartory and Grobbelaar 1984, Knowlton 1984). Sampling and analytical methodology were consistent throughout.

Lake survey data were submitted to a random effects ANOVA applied to individual reservoirs (Snedecor and Cochran 1980) to quantify two components of variation: variation among sampling dates within individual summer seasons (seasonal variation) and variation in seasonal averages from one year to another (year-to-year variation). This analysis follows Knowlton *et al.* (1984) except for the omission of a minor adjustment for sampling error due to variation among replicate subsamples. Seasonal and year-to-year variation are equivalent to the simulation parameters V_s and V_y, respectively, and median values were used in the simulations. Similarly large-scale estimates of autocorrelation parameters, V_e and ρ were lacking, but initial values were obtained from analysis of eight seasonal data sets, each based on sampling over 108 consecutive days. Six of these were from Lake Woodrail, a small impoundment in Columbia, Missouri, which was sampled daily from 19 May 1992 through 19 December 1996 (TP, TN and Chl only; Jones and Knowlton 2005). Lake Woodrail, together with Little Dixie and Rocky Fork lakes, were also sampled daily from 13 May through 27 August 2004. Autocorrelation parameters were obtained from these time series using PROC AUTOREG in SAS and averaged as starting values for V_e and ρ. These estimates were then adjusted incrementally until median values of seasonal and year-to-year variation produced by simulations under the "no change" scenario matched median estimates from the 1085 lake-years of survey data.

All data were transformed to base$_{10}$ logarithms before analysis and simulations conducted on a log$_{10}$ scale, except that expected values (LEV and AEV) were estimated before transformation so that changes over time would be linear (arithmetic). All simulations were repeated 1000 times with median values presented in the results. Simulated temporal trends were tested with ordinary least-squares regression. Simulations and other analyses were conducted using PC-SAS (version 8.02). Variability estimates and confidence limits in this analysis are in log10 units. To provide a familiar scale, variance is expressed in the text as approximate coefficients of variation ("CV") scaled as a percent of the mean and calculated as:

$$\text{"CV"} = 50 \times [(10^{v} - 1) + (1 - 10^{-v})]$$

where v = V_y, V_s or V_e (Knowlton *et al.* 1984). "CV"'s represent an averaging of the arithmetically asymmetrical tails produced by back-transformation. For example, ±0.108 in $\log_{10}$ units back-transforms to 0.78 (-22%) and 1.28 (+28%), which average to ±25%.

Results

Parameters used in simulations (Table 1) differed among the four trophic state variables simulated. Median seasonal and year-to-year variation for Chl was more than twice that for TN, with TP and SD intermediate. Seasonal variation (within individual summers) was greater than year-to-year variation (among summer seasons over time) for all four variables. With one exception, values of autocorrelation parameters used in simulations were greater than average estimates from lakes Woodrail, Little Dixie and Rocky Fork (Table 2). In the cases of error variance (V_e) for TN and the autocorrelation coefficient (ρ) for TN and SD, values obtained by iteration were above the range of the measured values. Given the small number of estimates available for this analysis (eight for TP, TN and Chl; three for SD) and the fact that six of the eight data sets were from one water body, this discrepancy is probably negligible.

Examples of 20-year time series of Chl data simulated under the "no change", "gradual change" and "abrupt change" scenarios (Fig. 2) illustrate the large magnitude of temporal variation characteristic of Missouri reservoirs. Within summers, order-of-magnitude variation of Chl is typical. In the eight data sets based on daily sampling, for example, the median seasonal variation in Chl (±57%) closely matched the state-wide median (±59%; Table 1). In these eight data sets (Fig. 3) the range of Chl in summer (maximum/minimum) averaged 18-fold (range 8-32-fold). In contrast, TN varied by an average slightly over two-fold (range 1.9-3.2-fold). The often extreme temporal variation of these variables tends to obscure gradual changes in average conditions (Fig. 2a) and interferes with quantification of lake trophic state.

Simulation 1 – Measuring Trophic State

Temporal variability in our data suggests observations over several summers are needed before the "average" condition of a lake can be reliably estimated. This inherent variation leads to the obvious question of how many samples per season over how many years must sampling continue to estimate the long-term means of TP, Chl, TN or SD within a given range? To address this question we simulated 20 consecutive summers of daily OVs under the "no change" scenario (Fig. 1a). From this series, subsamples of OVs were taken at rates of 3, 6 or 16 samples per season in consecutive years. Means and 95% confidence limits (CL_{95}) were calculated by first

Table 1.-Medians of seasonal and year-to-year variance in lake survey data (as approximate coefficients of variation) used as parameters in Monte Carlo simulations. Data are from 116 Missouri reservoirs (1085 lake-years).

	Seasonal (V_s)	Year-to-year (V_y)
TP	30%	20%
TN	21%	12%
Chl	59%	25%
SD	35%	19%

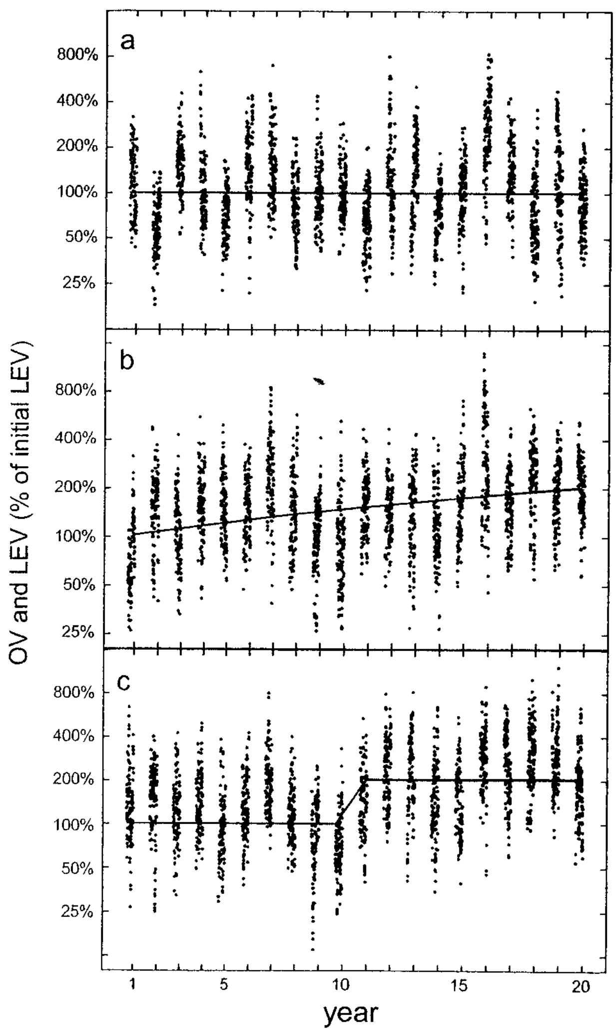

Figure 2.-Examples of simulated 20-year series of 16 May-31 August data based on median variability of Chl. Solid lines are the long-term expected values (LEV's). (a) no change scenario; (b) gradual scenario (doubling over 20 years); (c) abrupt scenario (doubling during two years).

Table 2.-Means and ranges of autocorrelation statistics from time-series data for lakes Woodrail, Rocky Fork and Little Dixie and autocorrelation values used in simulations.

		autocorrelation (ρ)			error variance (V_e)		
	n	mean	range	simulation	mean	range	simulation
TP	8	0.71	0.32-0.89	0.84	14%	10-63%	16%
TN	8	0.53	0.30-0.69	0.71	12%	9-14%	15%
Chl	8	0.73	0.47-0.86	0.83	33%	23-51%	32%
SD	3	0.67	0.58-0.71	0.85	15%	11-19%	19%

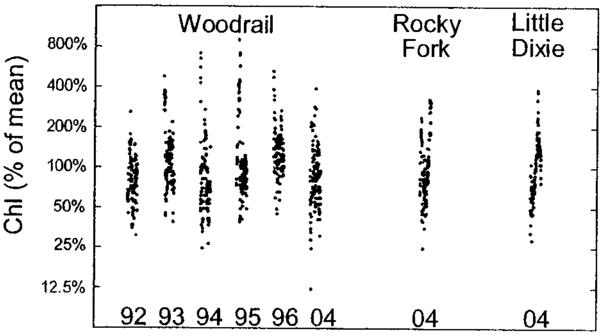

Figure 3.-Time series of summer Chl (as % of mean Chl) in daily samples from lakes Woodrail (1992-1996, 2004), Rocky Fork (2004) and Little Dixie (2004).

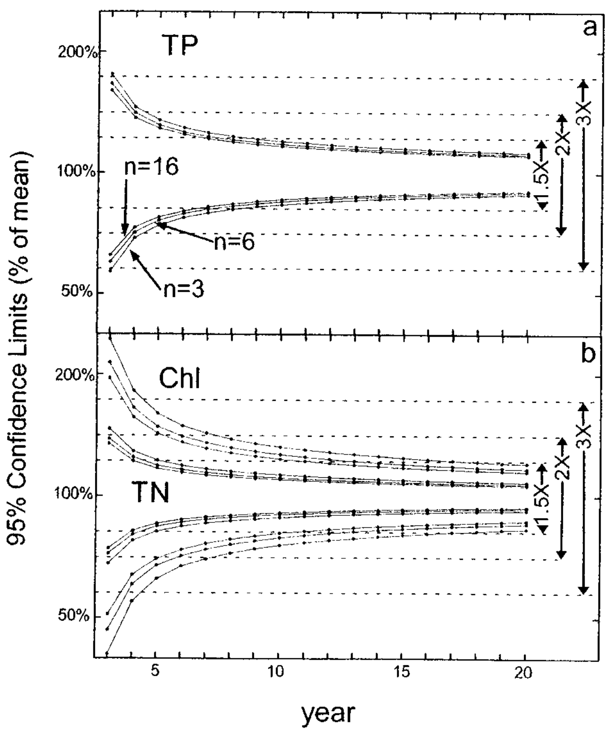

Figure 4.-Upper and lower 95% confidence limits as a function of years sampled and sampling frequency for simulations of TP (a) and TN and Chl (b) under the "no change" scenario. Each data point represents the median of 1000 simulations. Reference lines show ranges of 1.5-, 2- and 3-fold between upper and lower confidence limits (upper/lower).

averaging data by summer and using these seasonal means to estimate the overall mean and CL_{95}.

Simulations of TP (Fig. 4a), show confidence intervals narrowing rapidly during the first 4-8 years and more gradually afterward. Chl, having the greatest variability both within and among years, yielded the worst precision. Confidence intervals for Chl were more than twice as wide as for TN (Fig. 4b) with TP and SD intermediate. With the lowest overall variability, TN could be estimated within a factor of two (upper CL_{95}/lower CL_{95}) with monthly sampling (n=3) over only four summers. For TP and SD, five summers would be required to achieve the same level of precision, and for Chl, eight summers would be needed (Fig. 4).

Chl had by far the greatest seasonal variance (Table 1) and thus benefited most from increasing within season sampling frequency. Compared to sampling monthly (n=3), sampling weekly (n=16) for Chl took two years off the time required to estimate the mean within a two fold range (Fig. 4b). For the other variables, however, weekly sampling saved only one year. For all four variables, increasing the span of years sampled improved precision much more efficiently than intensifying sampling within seasons. For example, 10 summers of monthly samples (30 total samples) was roughly equivalent to seven summers of weekly samples (112 total samples) for all four variables.

Simulation 2 – Detecting Changes

A major function of lake monitoring is to detect changes over time. In a second set of simulations we created series of OVs based on gradually or abruptly changing expected values (*e.g.*, Fig. 1) and subsampled the daily OVs at rates of 3, 6, or 16 times per season in consecutive years. A seasonal mean was calculated for each year and regression analysis, with time as the independent variable, used to determine significant trends among seasonal means.

In a reservoir with median variability, the gradual doubling of a trophic state variable over 20 years is a trend that may not stand out clearly against the background of seasonal and year-to-year variation (*e.g.*, Fig. 2b). Thus, in our simulations, sampling proceeded for 11 to >20 years, depending on the trophic state parameter and sampling intensity, before regressions had a high (>75%) probability of detecting the increase (Fig. 5). Differences in sampling intensity had similar effects on TN, TP and SD. The number of years required to achieve a 75% detection rate decreased by two when sampling frequency increased from monthly to weekly. With monthly sampling, a 75% detection rate required 13 years for TN and 17 years for TP and SD. For Chl, 20 years of monthly sampling provided only a 57% probability of detecting the trend, compared with probabilities of 73% and 81% for semi-monthly and weekly sampling, respectively (Fig. 5).

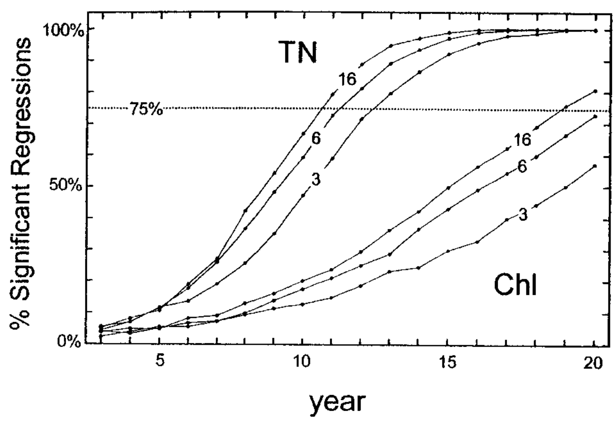

Figure 5.-Percent of simple regressions showing significant ($p<0.05$) increases in seasonal mean TN or Chl over time as a function of years sampled and sampling frequency simulated under conditions of the "gradual change" scenario (doubling over 20 years).

In comparison with gradual changes, an abrupt change (Fig. 2c) was more readily detected, provided sufficient data were collected prior to the onset of change. For a two-fold increase occurring in the middle of 20-year time series (during years 10 and 11), the trend was likely detected (>75% probability) the second year after the change was complete for TN (Fig. 6a) and in the third year after the change for TP and SD (Table 3), irrespective of sampling frequency. For Chl, the 75% threshold was achieved 4, 5, and 7 years after the change for weekly, semi-monthly and monthly sampling frequencies, respectively, (Fig. 6a).

Probability of detecting an abrupt change, however, partly depended on the span of sampling prior to the change. If only two years of data were collected before the change, no amount of subsequent sampling would provide more than ≈70% chance of detection for TP, SD or Chl (*e.g.*, Fig. 6b). The low temporal variability of TN, however, would allow detection of change within only 2-3 years of its completion (Fig. 6b). For TP and SD at least three summers of pre-change data were required to insure that subsequent sampling would eventually have a high (>75%) probability of detecting change. With weekly sampling of Chl, a minimum of four years of pre-change data would be required, but with semi-monthly and monthly sampling, pre-change data from at least five and six years, respectively, would be needed and the detection rate would not exceed 75% until six years after the change occurred (Table 3).

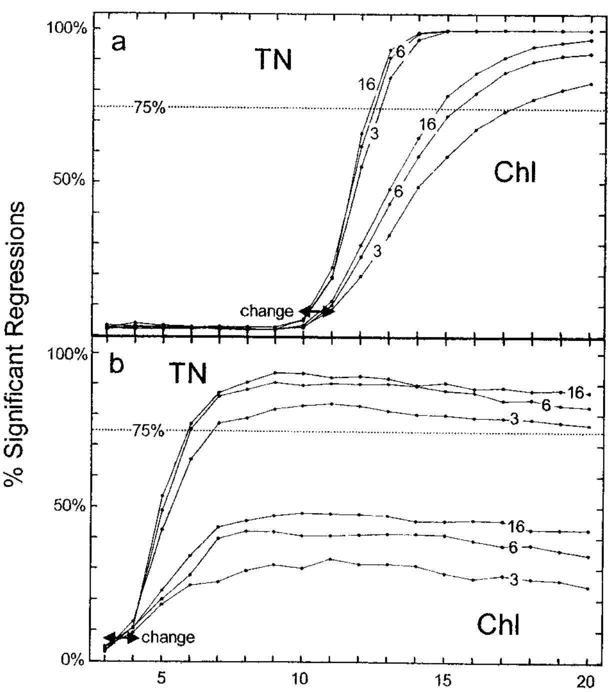

Figure 6.-Percent of simple regressions showing significant ($p<0.05$) increases in seasonal mean TN or Chl over time as a function of years sampled and sampling frequency simulated under conditions of the "abrupt change" scenario (doubling over two years). (a) Increase occurring in years 10 and 11 of the 20 year series; (b) Increase occurring in years 3 and 4 of the 20 year series.

Discussion

Variance in Other Regions

All lakes in this study are artificial impoundments. To assess whether temporal variation in these water bodies is similar to natural lakes and reservoirs in other regions, estimates of seasonal and year-to-year variation were compiled from other multi-lake studies. We were unable to find comparable estimates of autocorrelation parameters (Table 2), although autocorrelation is a well known feature of limnological time series (Prairie and Duarte 1996).

Table 3.-Years of pre-change and post-change sampling required to reach a 75% probability of detecting a significant change by simple regression (positive slope, $p<0.05$) in simulations of an abrupt two-fold increase over two years given different within-season sampling frequencies. The infinity symbol (∞) indicates that probability becomes asymptotic at <75%. Total years of sampling equal two plus the sum of pre- and post-change years.

	years of pre-change data	years of post-change data to reach 75% detection rate		
		monthly n=3	semi-monthly n=6	weekly n=16
TP	2	∞	∞	∞
	3	5	4	3
	9	3	3	3
TN	2	3	2	2
	9	2	2	2
Chl	2	∞	∞	∞
	4	∞	∞	6
	5	∞	6	4
	6	11	5	5
	9	7	5	4
SD	2	∞	∞	∞
	3	∞	4	3
	9	3	3	3

In some instances authors estimated seasonal (June-August or April-October) variances with untransformed data and presented regression models depicting the relationship of variance to the mean. Walker (1985), Marshall *et al.* (1988), and France and Peters (1992) have all published variance-mean regression models for Chl or TP for north-temperate natural lakes. In each case, seasonal variation in Missouri reservoirs was significantly less (paired t-test, $p<0.001$) than predicted by the published models. For Chl, the models of Walker (1985), Marshall *et al.* (1988), and France and Peters (1992) overestimated seasonal variation by median amounts of 5%, 14% and 5%, respectively, calculated as the difference between predicted and observed "CV"s. For TP, the France and Peters (1992) model overestimated seasonal variance by a median of 5%. These median differences were small compared to the huge range of individual values, suggesting seasonal variance in Missouri reservoirs is comparable to that in the natural lakes included in these studies.

Other authors provided median or mean estimates of variance in tables, figures or in the text. We recalculated these variances as "CV" values (Table 4). For studies in which year-to-year variation was decomposed into coherent (synchronous variation among lakes in a group) and lake-specific variance (Larsen *et al.* 1995, 2001) we summed the two components to estimate year-to-year variance. Most published variances were in natural log or $\log_{10}$ units, but Larsen *et al.* (1995) used untransformed data for SD so we calculated conventional coefficients of variation (square root of variance/mean) for this comparison.

Several estimates of seasonal and year-to-year variance were available for TP, Chl and SD. Only one other study (Florida lakes; Terrell *et al.* 2000) provided variance estimates for TN. Among the other studies cited, many differences in specific sampling and analytical techniques arise, but all were based on seasonal (mostly summer) samples except the study of Terrell *et al.* (2000), which involved year-around sampling.

Except for TN, all variance estimates covered wide ranges. This finding was especially true for year-to-year variance of Chl, which ranged from ±14% for Northeastern lakes sampled in the EMAP study (Larsen *et al.* 2001) to ±76% for New York lakes as presented in Larsen *et al.* (1995). In most studies, Chl had higher variance than TP or SD. In Florida, as in this study, TN had lower seasonal and year-to-year variation than the other parameters.

In general, variance estimates for Missouri reservoirs were well within the range of other studies except for seasonal variation of SD, which was ±6% greater than the next highest value. Among the four parameters, median year-to-year variation for Missouri reservoirs ranged from ±12% for TN to ±25% for Chl (Table 1). Among the data for other regions, only two of 23 estimates of year-to-year variance (Florida excluded) were below this range, while seven of 23 were above. As demonstrated by the preceding simulations, year-to-year variance is crucial to the precision of lake monitoring data. Based on this interregional comparison, the median values for Missouri seem to cover a large part of the likely range of year-to-year variance for this group of parameters, but may be somewhat conservative except for SD. Thus our analysis based on Missouri medians seems unlikely to overstate the importance of temporal variance.

Table 4.-Seasonal and year-to-year variance as "CV"s from this study and the literature.

	TP		Chl		SD	
	V_s	V_y	V_s	V_y	V_s	V_y
Missouri, Iowa, Minnesota[a]	27%	13%	45%	20%		
CE Reservoirs[b]			39%			
Vermont[c]		14%	44%	23%	17%	9%
Minnesota[d]	25%		49%		18%	
CE Reservoirs[d]	27%		64%		28%	
Vermont[e]		34%	49%	44%	17%	17%
New York[e]	41%	21%	73%	76%	24%	22%
Minnesota[e]	54%	36%	44%	45%	26%	19%
Maine[e]	20%	20%	62%	35%	16%	12%
Florida[f]	28%	<14%	52%	<22%	24%	<14%
Northeastern U.S.A.[g]	41%	40%	68%	14%	29%	0%
This Study	30%	20%	59%	25%	35%	19%

[a] From Table 3 in Knowlton *et al.* 1984; June-September data from 121 reservoirs and 67 natural lakes, 313 lake-years 1-6 years per lake.

[b] From Table 2 in Walker 1985, April-October data from Corps of Engineers reservoirs, 258 station-years.

[c] From Figure 5 in Smeltzer *et al.* 1989; Spring TP data (125 lakes, 738 lake-years, 2-11 years per lake), June-August Chl (55 lakes, 298 lake-years, 1-11 years) and SD (56 lakes, 335 lake years, 1-9 years per lake).

[d] From Figure 7 in Smeltzer *et al.* 1989.

[e] From Figure 2, Table 4 and Table 3 in Larsen *et al.* 1995; July-August data, 7-86 lakes, 32-774 lake-years, 4-11 years per lake depending on state and parameter. CV's for SD are arithmetic coefficients of variation estimated from variance (untransformed data) and mean SD. Year-to-year variance taken as the sum of "year" and "lake × year" variances, seasonal variance taken as "index" variance.

[f] From page 192 in Terrell *et al.* 2000; Year-round data from 71 lakes, 4-11 years per lake. Year-to-year variation was not corrected for seasonal variation and is thus less than stated. Seasonal and year-to-year variance for TN was also given as ±19% and ±11%, respectively.

[g] From Table 2 in Larsen *et al.* 2001; July-August data from a random sampling of lakes in New England, New York and New Jersey in the EPA Environmental Monitoring and Assessment Program (EMAP). Year-to-year variance taken as the sum of "year" and "interaction" variances, seasonal variance taken as "residual" variance.

Trophic State Assessment and Monitoring

The doubling (or halving) of trophic state variables like TP or CHL seems like a change that should be detected by routine lake monitoring programs. The logic of a factor-of-two scale was incorporated in the Carlson trophic state index, where each 10-point decade represents a doubling of algal biomass (Carlson 1977) and is a recognized metric in lake management. But factor-of-two fluctuations are a fraction of the ordinary "noise" of short-term temporal variability in lakes. In our data sets based on daily samples (Fig. 2), Chl usually varied by >10-fold during May-August, and these results seem typical. Given the potentially large variability of rainfall and other external conditions, year-to-year fluctuations must also be expected (de Hoyos and Comín 1999). Distinguishing a real change in lake trophic state requires measurements encompassing enough "ordinary" variation to assess the long-term average condition of the lake. How large is "ordinary" variation and what does that imply about quantifying lake trophic state?

Temporal variability during summer, "seasonal variability," has been quantified in several studies representing thousands of lake-years (Trautmann *et al.* 1982, Knowlton *et al.* 1984, Walker 1985, Marshall *et al.* 1988, Smeltzer *et al.* 1989, France and Peters 1992, Larsen *et al.* 1995, 2001, Terrell *et al.* 2000). Published median or average estimates of variance are mostly within a factor-of-two range for a given parameter (Table 4), with Missouri reservoirs approximating the range for other regions. In quantifying trophic state, however, seasonal variation is less an impediment than variation among years. Obviously, the number of years of data needed to measure trophic state depends on the magnitude of year-to-year fluctuations. Year-to-year variance, however, is more difficult to quantify than seasonal variability because long term data sets spanning several years per lake are required. Also, year-to-year variance measures variability among seasonal averages estimated with (often large) uncertainty. Consequently, estimates of year-to-year variance are quite imprecise (Knowlton *et al.* 1984); therefore, published estimates of year-to-year variability are less consistent than those for seasonal variance, spanning ranges of three-fold or greater (Table 4). Much more information of this type is needed before a clear assessment can be made of truly typical amounts of "ordinary" variation. At present, we can only look at what seems to be representative range.

In the Missouri data, TN has low temporal variability comparable to some of the lower variability estimates for TP and SD depth in the literature (Table 4). For a parameter with low variability, results of our simulations suggest measuring trophic state within a two-fold range (95% confidence interval; Fig. 4) would typically require as few as 12 total samples (three per summer over four summers). With low variability, an abrupt two-fold increase in a parameter (Fig. 6) would be readily detected soon after it occurred, even with a minimal amount (two summers) of pre-change data. In contrast, gradual changes are inherently difficult to detect in variable systems. In our "gradual change" simulation (Fig. 5) TN increased by >50%, 11 years into the transition, before weekly sampling in consecutive summers (176 total samples) provided a high probability of detecting a change.

Chl had the highest temporal variability of the trophic state parameters. In simulations, measuring mean Chl within a factor of two required about twice as much data as did TN. Three samples per summer for eight years or six samples per summer for six years were required (Fig. 4), and detecting changes was correspondingly more difficult. Detecting an abrupt doubling of Chl required more observations before and after the change than TN (Fig. 6), and a gradual doubling of Chl over 20 years was not readily detectable with monthly or twice-monthly sampling until after the change was complete (Fig. 5). Given that mean Chl is often used to assess lake trophic state and is the key response variable to eutrophication, it is discouraging to consider the potential difficulty of detecting its change. Additionally discouraging is that year-to-year variation of Chl in Missouri was much less than in some published estimates (Table 4). It seems that determining average Chl within a factor of two maybe a large undertaking for some lakes.

An obvious practical implication of these results is that multiple years of data are needed to provide even moderately precise assessments of lake trophic state. Estimating TP within a factor of two is a reasonable goal for a minimal assessment. Our simulations show that five summers of monthly samples (15 total observations) represents the smallest commitment of resources required to reach that goal in a lake of typical variability. Six summers of monthly samples, the minimum recommended by Molot and Dillon (1991), would usually estimate TP within ±25% (a 1.67-fold range). But these estimates are based on median variances, so we can assume that these sampling regimes be adequate for only half the lakes considered. For TP, a third of Missouri reservoirs exhibited year-to-year variance greater than the median for Chl (Table 1) and would require correspondingly more data (>8 summers of monthly samples) to reach the factor-of-two goal. The Missouri data are largely based on monthly samples, and 38% of reservoirs with ≤ 7 summers of data (n=37) have confidence intervals for TP >2-fold, whereas 99% of impoundments with ≥ 8 years of observations (n=79) have confidence intervals less than two-fold. Thus broadly applying even a minimal standard of precision for trophic state assessment is likely to require long-term monitoring.

Another practical implication is that changes in lake trophic state are not likely to stand out clearly from the noise of ordinary variation unless they are large or rapid. Some classic instances of trophic state alterations have been both. In Lake Washington summer SD decreased by nearly half during the 1950s and by half again during the early 1960s with increased inputs of wastewater (Edmondson 1972). SD subsequently increased by >5-fold in the decade following wastewater diversion (Edmondson 1994). Of 16 lakes cited by Sas (1989) showing significant declines in phosphorus resulting from loading reductions, all but two changed at rates greater than 3.5% per year (two-fold over 20 years), and the median rate of change was 8.2% per year (4.8-fold over 20 years). In screening lake-survey data sets for this analysis two reservoirs were excluded, Henry Sever and Little Dixie, because of management manipulations. Both showed large responses to grass carp stocking to control macrophytes wherein TP more than doubled over 6-7 years as macrophytes were reduced. In Henry Sever, Chl increased >6-fold during the same period. Such dramatic changes are likely noticed even in highly variable systems, but small or gradual changes are not. Our findings support the view of Smeltzer *et al.* (1989) that lake monitoring data should not be relied on for the detection of small changes in temporally variable parameters. Clearly, from the standpoint of many lake management questions, the answer to "how many samples are needed" is "as many as you can afford to get," or possibly "more than you can afford to get." Temporal variation is a limiting factor of great practical consequence in lake assessment.

As data on temporal variability accumulate, the limitations imposed may be remedied by quantifying causes or finding close correlates with predictive value. Published data (Table 4) suggest that temporal variation may vary consistently among regions. Work in other areas (Magnuson *et al.* 1990, Larsen *et al.* 1995) provides evidence of coherent, or synchronous, variations among lakes within regions. Time series from intensively studied lakes sometime reveal links between year-to-year variation and measurable external factor such as climate. For example, conditions in Castle Lake, California respond to El Niño events, and Lake Tahoe is affected by the intensity of spring storms (Jassby 1998). Reservoirs seem particularly likely to respond to variation in inflows (Knowlton and Jones 1995, Harris and Baxter 1997). Knowing the causes of variation, even if they are not predictable in advance, could permit after-the-fact adjustment of annual means to reflect a standard (and less variable) condition. Achieving a better understanding of "typical" temporal variability promises to provide many benefits to the management of lakes and protection of water quality.

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