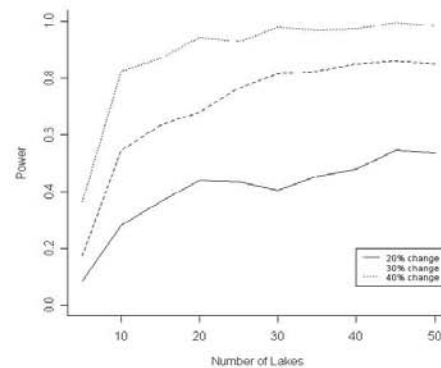




Lake Chemistry Power Analysis for the Sierra Nevada Network, National Park Service

Natural Resource Technical Report NPS/SIEN/NRTR—2012/621



$$y_{ijk} = \mu + w_j \beta + b_j + a_i + w_j t_i + c_{ij} + e_{ijk},$$

$$H_O : \beta = \frac{1}{m_b} \log(1 + \delta^*) \text{ or } \beta = \frac{1}{m_b} \log(1 - \delta^*)$$

$$H_A : \beta \neq \frac{1}{m_b} \log(1 + \delta^*) \text{ or } \beta \neq \frac{1}{m_b} \log(1 - \delta^*)$$



ON THE COVER

Photos of sampling at lakes in the Sierra Nevada Network and graphs and equations from the power analysis.
Photographs by: National Park Service

Lake Chemistry Power Analysis for the Sierra Nevada Network, National Park Service

Natural Resource Technical Report NPS/SIEN/NRTR—2012/621

Leigh Ann Harrod Starcevich

Oregon State University
Department of Statistics
P.O. Box 1032
Corvallis, OR 97339

September 2012

U.S. Department of the Interior
National Park Service
Natural Resource Stewardship and Science
Fort Collins, Colorado

The National Park Service, Natural Resource Stewardship and Science office in Fort Collins, Colorado publishes a range of reports that address natural resource topics of interest and applicability to a broad audience in the National Park Service and others in natural resource management, including scientists, conservation and environmental constituencies, and the public.

The Natural Resource Technical Report Series is used to disseminate results of scientific studies in the physical, biological, and social sciences for both the advancement of science and the achievement of the National Park Service mission. The series provides contributors with a forum for displaying comprehensive data that are often deleted from journals because of page limitations.

All manuscripts in the series receive the appropriate level of peer review to ensure that the information is scientifically credible, technically accurate, appropriately written for the intended audience, and designed and published in a professional manner. This report received formal, high-level peer review based on the importance of its content, or its potentially controversial or precedent-setting nature. Peer review was conducted by highly qualified individuals with subject area technical expertise and was overseen by a peer review manager.

Views, statements, findings, conclusions, recommendations, and data in this report do not necessarily reflect views and policies of the National Park Service, U.S. Department of the Interior. Mention of trade names or commercial products does not constitute endorsement or recommendation for use by the U.S. Government.

This report is available from the Sierra Nevada Network Inventory and Monitoring Program at (<http://science.nature.nps.gov/im/units/sien/>) and the Natural Resource Publications Management website (<http://www.nature.nps.gov/publications/nrpm/>) on the internet.

Please cite this publication as:

Starcevich, L. A. H. 2012. Lake chemistry power analysis for the Sierra Nevada Network, National Park Service. Natural Resource Technical Report NPS/SIEN/NRTR—2012/621. National Park Service, Fort Collins, Colorado.

Contents

	Page
Figures.....	v
Tables.....	vii
Appendixes	ix
Abstract.....	1
Introduction.....	1
Pilot Data	1
Power Analysis Goals.....	2
Membership Design.....	3
Revisit Design.....	4
Nonsampling Error.....	7
Nonresponse Error	7
Frame Error.....	7
Measurement Error	8
Methods	11
Results.....	11
Analysis Methods.....	13
Modeling the Trend and Variance Components	13
Simulating the Population.....	15
Calculating Power.....	16
Discussion	29
Literature Cited	31

Figures

	Page
Figure 1. Four revisit designs examined in the power analysis.	6
Figure 2. Power of trend detection for changes in fall specific conductance for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	24
Figure 3. Power of trend detection for changes in fall ANC for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	24
Figure 4. Power of trend detection for changes in fall NO ₃ for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	24
Figure 5. Power of trend detection for changes in fall SO ₄ for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	24
Figure 6. Power of trend detection for changes in fall PN for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	25
Figure 7. Power of trend detection for changes in fall PP for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	25
Figure 8. Power of trend detection for changes in fall pH for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	25
Figure 9. Power of trend detection for changes in fall Ca for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	25
Figure 10. Power of trend detection for changes in fall Na for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	26
Figure 11. Power of trend detection for changes in fall Mg for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	26
Figure 12. Power of trend detection for changes in fall K for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	26
Figure 13. Power of trend detection for changes in fall Cl for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	26
Figure 14. Power of trend detection for changes in fall temperature for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	27
Figure 15. Power of trend detection for changes in fall DON for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	27

Figures (continued)

	Page
Figure 16. Power of trend detection for changes in fall PC for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	27
Figure 17. Power of trend detection for changes in fall TDP for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].	27

Tables

	Page
Table 1. Minimum detection limits by analyte.	8
Table 2. Covariates corresponding to the Western Lakes data set.	11
Table 3. Power analysis inputs of fixed effects and variance components.....	16
Table 4. Net change and corresponding annual multiplicative change.	18
Table 5. Power of trend detection for 10- and 30- year trends at three levels of change.	19
Table 6. Power of trend detection for 10- and 30- year trends at four levels of change.	19
Table 7. Fall specific conductance power, 25 lakes, [(1-0),(2-3)] revisit design.	20
Table 8. Fall ANC power, 25 lakes, [(1-0),(2-3)] revisit design.	20
Table 9. Fall NO ₃ power, 25 lakes, [(1-0),(2-3)] revisit design.....	20
Table 10. Fall SO ₄ power, 25 lakes, [(1-0),(2-3)] revisit design.	20
Table 11. Fall PN power, 25 lakes, [(1-0),(2-3)] revisit design.....	21
Table 12. Fall PP power, 25 lakes, [(1-0),(2-3)] revisit design.	21
Table 13. Fall pH power, 25 lakes, [(1-0),(2-3)] revisit design.	21
Table 14. Fall Ca power, 25 lakes, [(1-0),(2-3)] revisit design.	21
Table 15. Fall Na power, 25 lakes, [(1-0),(2-3)] revisit design.	22
Table 16: Fall Mg power, 25 lakes, [(1-0),(2-3)] revisit design.	22
Table 17: Fall K power, 25 lakes, [(1-0),(2-3)] revisit design.....	22
Table 18. Fall Cl power, 25 lakes, [(1-0),(2-3)] revisit design.	22
Table 19. Fall temperature power, 25 lakes, [(1-0),(2-3)] revisit design.....	23
Table 20. Fall DON power, 25 lakes, [(1-0),(2-3)] revisit design.	23
Table 21. Fall PC power, 25 lakes, [(1-0),(2-3)] revisit design.	23
Table 22. Fall TDP power, 25 lakes, [(1-0),(2-3)] revisit design.	23

Appendixes

	Page
Appendix A: Comparison of Power Plots for Uncensored Data and for Data that Were Left-Censored and Adjusted by Multiple Imputation	33
Figures	33
Appendix B: Power Plots for Six Analytes and Four Revisit Designs	39
Figures	39
Appendix C: Power Tables for Six Analytes and Four Revisit Designs	71
Tables	71

Abstract

A power analysis to determine the power to detect trend in lake chemistry analytes over time was conducted to inform development of the Sierra Nevada Network (SIEN) Lake Monitoring Protocol. Pilot data from two surveys of Sierra Nevada lakes are used to examine the power to detect trend with Monte Carlo power simulation. Trend analysis of sixteen analytes exhibiting a range of variation composition is conducted with a linear mixed model on the logarithmically-transformed metrics. The power to detect trend does not differ appreciably among four temporal revisit designs examined in this power analysis. Trends in specific conductance and pH are detected with the highest power because these analytes exhibit very low year-to-year variation and low variation among site-specific slopes. The power to detect linear trend may be improved by incorporating covariates to explain variation and identifying subpopulations exhibiting similar trend.

Introduction

The Sierra Nevada Network (SIEN), part of the National Park Service (NPS) Inventory and Monitoring (I&M) program, is developing a protocol for annual monitoring of lake chemistry indicators. The purpose of the I&M program is to develop and provide scientifically sound information on the current status and long-term trends in the composition, structure, and function of park ecosystems, and to determine how well current management practices are sustaining those ecosystems. In order to assist the network in setting realistic long-term monitoring goals, a power analysis was conducted to determine the power to detect trend in lake chemistry analytes over time. Power analyses are helpful in determining sample sizes that will provide information to detect changes in the population of interest over time at the desired level of change. Factors such as sample membership design, revisit designs over time, detection limits, and components of variation were considered when conducting this power analysis. SIEN personnel want to detect trends in lake chemistry outcomes with power of 0.8.

Pilot Data

Two data sets were used for the power analysis of SIEN lake chemistry surveys: the Seven Lakes survey conducted by the University of California – Santa Barbara (Melack et al. 1998) and the Western Lakes survey conducted by the US EPA in 1985 (Eilers et al. 1989) and again in 1999 (Clow et al. 2002). The Seven Lakes survey consisted of a judgment sample of seven important lakes in SIEN and was conducted for up to 19 years ranging from 1982 through 2000.

Measurements from both the epilimnion and the outflow of each lake are available from this study. The Western Lakes survey was based on a probability sample of 46 lakes in 1985, 29 of which were revisited in 1999. Given the differences in the two studies, the Seven Lakes study data is expected to provide more accurate information on sources of temporal variation while the Western Lakes study will be more spatially representative of the population of interest.

The lake chemistry survey will consist of a sample of lakes in SIEN. Because only one or two measurements will be taken from each lake during the SIEN water chemistry survey, means of outflow and epilimnion measurements from pilot data were used for modeling. Sixteen outcomes of interest were chosen for the power analysis: specific conductance (Spec Cond), acid neutralizing capacity (ANC), sulfates (SO_4), nitrates (NO_3), particulate phosphorus (PP), particulate nitrogen (PN), pH, calcium (Ca), sodium (Na), magnesium (Mg), potassium (K), chloride (Cl), temperature, dissolved organic nitrogen (DON), particulate carbon (PC), and total dissolved phosphorus (TDP). Of these 16 analytes, the first six were used for more intensive analyses to determine what types of survey design and analysis issues might affect power.

Power Analysis Goals

Annual surveys of lake chemistry will be used to obtain estimates of lake chemistry status and trend. Trend may be defined in a number of ways, and definitions should be clarified so that survey goals are clear. Surveys conducted over time may be used for estimation at particular points in time, to estimate average parameters over time, to measure net or annual change in a population, to measure factors contributing to individual change, or to measure durations of events (MacDonald 2003). Individual change is measured at the level of the sampling unit. The measurement of net change includes all sources of change and is measured at the scale of the population. Therefore, individual change does not necessarily imply net change because trends at individual sites may vary and result in no net change.

This power analysis will target net change in the population. Net change may also be expressed in annual change so that power approximations for different time spans may be more directly compared. The detected population change will be measured in linear trend for an outcome transformed to the logarithmic scale; back-transformed estimates of trend will provide estimates of exponential growth or decay of the median response. We adopt the perspective of Urquhart and Kincaid (1999) that trend is directional, not cyclic, change. We agree that trend can often be nonlinear, but in the sense of Urquhart and Kincaid (1999), a directional change will have some linear component and deviations from the linear trend. The goal of this power analysis is to examine the power to detect linear trend in the logged outcome as a function of the annual sample size of sites or the monitoring period length in years for a set of water chemistry outcomes, several revisit designs, and a range of net trends. A benefit of using simulations for power analysis is the straightforward implementation of revisit designs in the analysis.

While estimates of status are also of interest, currently no test of status has been defined for which to assess power. Eventually, park managers will want to test the proportion of lakes that fall above or below a particular threshold. After three years of monitoring data are available, reasonable threshold levels will be determined. Therefore, power for testing status will not be pursued in this report.

Survey Design Considerations

The survey design specifies the selection mechanism and timing of the survey and should complement the goals of the monitoring program. These factors affect the estimates obtained from survey data, so aspects of the survey design such as the membership design and the revisit design should, when possible, be incorporated into the power analysis so that power is accurately estimated.

Membership Design

The SIEN work group has discussed a variety of membership designs for the lake chemistry survey. The membership design specifies how the units in the sample are chosen (MacDonald 2003). Membership designs that were under consideration included the simple random sample, variable probability sampling based on an index of cost to survey a particular site, and generalized random tessellation stratified design (GRTS).

A simple random sample is the easiest design to implement from the sample-drawing perspective but may result in a sample that is ill-distributed across the area of interest. Sampled lakes may be clustered, resulting in an inefficient sample for long-term monitoring because information is essentially repeated within the cluster (MacDonald 2003). Sites may be chosen that are far from paths and not easily accessible, causing increased survey costs and potential bias if the sites are inaccessible. Analysis methods are generally straightforward for simple random sampling in the absence of complications.

Variable probability sampling in the SIEN lake chemistry would be based on a cost-surface model that would compute the approximate travel time to a site based on factors such as trail distance, vegetation types, and slope. Data from GIS layers would be used to compute the travel time to each site; the inclusion probability for each site would be inversely proportional to this time. This membership design could be structured to include lakes that are closer to trails and trailheads and less costly to access. However, lakes that are farther away would have some nonzero probability of inclusion and would be included in higher numbers as sample sizes increase. This design could also be used to ensure that lakes that are far from trails are included with a certain probability. The variable inclusion probabilities ideally should be incorporated into analyses techniques or estimates will be biased.

The GRTS design employs a systematic sampling approach along a randomly ordered sequence of location addresses to obtain a spatially balanced probability sample (Stevens and Olsen 2003). The primary benefit of the GRTS design is spatial coverage of sampled points across the sampled population. The list of sampled points that is generated by the GRTS library developed in R, “spsurvey” (Kincaid 2006), provides spatial coverage if points are visited sequentially. Therefore, if funds or time elapse before the full sample is achieved, a sequential sample of points will still be spatially balanced. Similarly, if more funds are made available late in the survey season or if some points could not be visited due to accessibility problems, a list of sample points that was drawn with additional points could be sampled and provide a spatially balanced sample. Variable probability sampling may also be incorporated into the GRTS design.

Analysis of GRTS sample data incorporates the neighborhood variance estimator which employs weights based on distances between sampled points within a neighborhood. The data analyst may define the size of a neighborhood based on the spatial density of sampled points or perceived spatial correlation. Points outside of the neighborhood are assumed to be independent. Neighborhood variance estimates were found to be 22% to 58% smaller than variances computed assuming an independent random sample (Stevens and Olsen 2003). Therefore, analysis assuming a simple random sample can be used with the knowledge that confidence intervals will be wider than necessary. Estimates of status would need to incorporate the neighborhood variance estimator.

The GRTS design is more complex than many sampling designs. Sample selection involves importing a GIS shapefile into the R workspace “spsurvey” or by implementing the ArcGIS geoprocessing toolbox, RRQRR, developed by Dave Theobald at Colorado State University. In both cases, if the sampled population area consists of an area with a high ratio of edge to area, sampled points can be distributed more toward the edge (Don Stevens, personal communication). Furthermore, if there are holes in the polygon where sampling is not conducted (areas outside the target population, inaccessible areas), then the R code must be altered. However, for standard population polygons, this membership design guarantees a level of spatial coverage that cannot be assumed with a simple random sample or variable probability sampling alone.

Revisit Design

The revisit design provides the structure of temporal sampling for the selected sites (MacDonald 2003). Sites are generally split into panels and panels may be visited annually or on a schedule. When a panel is sampled, all sites within a panel are visited within the same year. Panel designs provide balanced replication of sites over time so that spatial and temporal effects may be modeled and trend may be accurately estimated.

Notation for panel designs will be as defined by MacDonald (2003). The notation uses a string of numbers, dashes, and commas to identify the revisit design among panels. The numbers in odd-numbered positions will designate the number of consecutive visits to a panel before it rotates out of the revisit schedule. Digits in the even-numbered positions indicate the number of sampling occasions that the panel will not be revisited. Therefore, a revisit schedule of [1-0] indicates that the panel will be revisited each year and never rotated out of the schedule. This revisit schedule is equivalent to taking a random sample of sites and visiting them every year. Differing revisit schedules among panels are indicated by separating the digits in parentheses by commas within the brackets. For example, a revisit schedule of [(1-0), (2-3)] indicates that the revisit design includes an annual panel that is revisited every year as well as a set of panels that are visited for two consecutive years then not visited for the following three years before being rotated back into the design.

Four revisit designs were examined in this power analysis and are presented in tabular format in Figure 1. The first revisit schedule is the [1-0] design in which all selected sites are visited every year. Among five revisit designs, Urquhart and Kincaid (1999) found this design to have the highest power for detecting linear trend. The other three revisit designs under study include an annual revisit panel with a suite of panels visited in rotation. The annual revisit panel provides connectedness in the membership design so that annual effects can be discerned from site-to-site

variation. Note that longer spans between panel revisits imply that more survey occasions are needed to visit the entire sample of sites and to obtain complete replication. The four revisit designs examined here, [1-0], [(1-0), (1-3)], [(1-0), (2-3)], and [(1-0), (2-5)], take 1, 4, 5, and 7 years, respectively, to visit all sites in the sample.

Revisit sites should be chosen by considering the outcome of interest and the time frame within which a trend estimate is desired. Periodicity in the outcome of interest should be considered when determining the time between survey visits for a panel. If measurements from sites are highly correlated between consecutive years, survey revisits may be spaced to avoid duplication of information unless the measurement of that correlation meets a specific monitoring goal. If trend estimates are needed within the next 5 to 10 years, then revisit designs with more frequent revisit patterns will be more desirable. Annual status estimates benefit from increased sample size within a given year. Consistent sampling over time improves trend estimates. Drawbacks of concentrating effort into a single park each year include longer required intervals for attaining adequate power to detect trend and potential confounding of park and year. These trade-offs are considered when selecting a revisit design and allocation of effort across panels of a revisit design. MacDonald (2003) cited several sources who indicated that the annual revisit panel should use roughly 50% of annual resources. However, Urquhart, et al. (1993) found that 10-20% of annual resources could be used for sites visited annually.

Figure 1. Four revisit designs examined in the power analysis.

Design [(1-0)]

Panel	Year							
	1	2	3	4	5	6	7	8
1	X	X	X	X	X	X	X	X

Design [(1-0),(1-3)]

	Year							
	1	2	3	4	5	6	7	8
1	X	X	X	X	X	X	X	X
2	X				X			
3		X				X		
4			X				X	
5				X				X

Design [(1-0),(2-3)]

Panel	Year									
	1	2	3	4	5	6	7	8	9	10
1	X	X	X	X	X	X	X	X	X	X
2	X	X				X	X			
3		X	X				X	X		
4			X	X				X	X	
5				X	X				X	X
6	X				X	X				X

Design [(1-0),(2-5)]

Panel	Year														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2	X	X						X	X						X
3		X	X						X	X					
4			X	X						X	X				
5				X	X						X	X			
6					X	X						X	X		
7						X	X						X	X	
8	X						X	X						X	X

Nonsampling Error

Nonsampling errors are errors that arise from the imperfect execution of the sampling design and include nonresponse error, frame error, and measurement error (Lessler and Kalsbeek 1992).

While these errors often cannot be avoided, precautions may be taken to minimize their impact and adjust for any potential bias of estimates during the analysis phase.

Nonresponse Error

Nonresponse error occurs when an incomplete response is obtained for a sampling unit.

Nonresponse error might be an issue for the lake chemistry survey if some lakes included in the sample are not surveyed due to time restraints or due to inaccessibility. If an inaccessible site is not surveyed for a reason that is associated with an outcome of interest, then estimates for that outcome may be biased due to nonresponse error. If nonresponse is expected, a larger sample size might be selected during the sample draw so that alternate sites are available and not subjectively chosen later. If full samples cannot be obtained, weighting approaches for nonresponse, such as the post-stratification adjustment and the weighting class adjustment (Oh and Scheuren, 1983), may be used to account for reduced samples.

Frame Error

Frame error occurs when the sampled population does not match the target population for which inference is desired. Since most of the information used to select sample sites comes from GIS layers, the integrity of the frame relies on the accuracy and completeness of the GIS information. Lakes are defined by the lake chemistry monitoring workgroup; the frame defining the sampled population should match this definition of the target population as closely as possible.

Monitoring ecologists should periodically reassess the sampling frame to ensure that sampled sites are indeed members of the target population and to determine if any lakes previously omitted from the target population should be reclassified and included in the inferential population. Personnel should determine a reasonable time interval for frame assessment based on knowledge of the lake system.

The use of a cost-surface model to develop variable probability sampling could be subject to considerable frame error if many GIS layers with varying levels of error are incorporated into the cost-surface model. Similarly, stratified random sampling based on an erroneous stratification could actually inflate variance estimates rather than provide the decrease in variance that is usually sought when employing stratification.

Measurement Error

Measurement error occurs when an incorrect measure of a unit is obtained. Measurement error can have many sources, such as observer error, instrument error, and detection error. One source of error that is common in water quality surveys is error by the analyzing laboratory in detecting dilute concentrations. These minimum detection limits (MDL) cause data to be left-censored because their values are subject to considerable variation and cannot be verified by the laboratory conducting the analysis. Helsel (2005) described a number of parametric and nonparametric approaches for accounting for left-censored data when summarizing data.

To determine if adjustments for left-censored data would affect the power to detect trend, simulated data below established MDL levels were treated as left-censored using the MDL levels given in Table 1. Because MDL levels may change over time and depend on the laboratory that is providing the chemical analysis, these limits are approximations. Missing data could not be distinguished from MDL data in the data sets because these levels were not archived over time. For more detailed future analysis, MDL levels should be archived over time for each analyte.

Table 1. Minimum detection limits by analyte.

Analyte	MDL
ANC	0.5000 µeq/l
NO ₃	0.0120 mg/l
SO ₄	0.0100 mg/l
PN	0.0001 mg/l
PP	0.0003 mg/l

Since the mixed model will be used to accommodate the revisit structure of the data and because single imputations of left-censored data are not recommended, a multiple imputation approach was applied in which a parametric model based on the observed data was used to generate random imputations of the left-censored data. The method is called the “maximum likelihood” method by Helsel (2005) and represents a more general version of the Tobit model. Trend analyses were conducted for each imputed data set and the estimates of trend and their variances were incorporated into a multiple imputation estimate of trend. This estimate was used in the evaluation of power.

Power plots for the unadjusted data set and for the data that were censored and imputed are given in Appendix A for analytes exhibiting left-censoring, with the exception of the highly variable NO₃ analyte. Power was evaluated for 200 iterations of each power curve; for such a small number of iterations, the power plots will exhibit some variation. However, the basic power curves are almost identical between the two sets of plots, indicating that the adjustment of left-censored data by multiple imputation does not affect the power to detect trend. Given that power is unaffected by this method and that simulation times are greatly increased by incorporating this method, the power analysis will not include an adjustment for left-censored data. However, future analysis of left-censored data will benefit from such adjustments if data are susceptible to minimum detection limits. Ultimately, using labs that can obtain the most precise measurements

of chemistry indicators with the lowest detection limits is the best defense against this source of measurement error.

The Kaplan-Meier (KM) approach was also considered, but this approach is not amenable to multiple stochastic regression imputation. Multiple imputation accounts for the variability in the predicted outcome by incorporating the distribution of the error term. Helsel (2005) recommends a sample size of 50 for the "maximum likelihood" approach but also cites work by Gleit (1985) and Shumway et al. (2002) indicating that poor performance occurs for samples below 25 to 50 (Helsel 2005). Since sample sizes of 25 lakes will be difficult to obtain each year in the SIEN lake chemistry survey, using this multiple imputation method for left-censored data may lead to problems. The seasonal Kendall test is commonly used for detecting trend and its multi-site analog, the regional Kendall test, could be used as a secondary measure of trend. The panel structure of the data will need to be ignored for this nonparametric approach, but this analysis may provide additional trend information to compare against the parametric approach combined with multiple imputation.

Incorporating Covariate Data

Several temporal and spatial covariates were available for the two pilot data sets to explain variation. The covariates used in this model selection exercise were obtained during the two pilot study and do not necessarily represent all covariates that affect trend. These covariates were included as explanatory variables in the fixed effects regression portion of the mixed model to determine if estimates of random effects variance components would be affected. If significant variation could be explained, power analyses could incorporate more accurate estimates of random effects.

Methods

For the Seven Lakes study, mean daily discharge data were available for Emerald, Pear, and Topaz Lakes and were incorporated into the mixed model. Gallegos and Berg (2007) identified and calculated several covariates for the data from the 29 lakes surveyed during the 1985 and 1999 in the Western Lakes study and are described in Table 2. Mixed model analysis in SAS (SAS Institute 2004) did not include the “NOBOUND” option so that non-negative estimates of random effects variances could be obtained.

Table 2. Covariates corresponding to the Western Lakes data set.

Covariate	Description
W	Wilderness class
EM	Elevation (m)
WS	Watershed area without lake (hectares)
LS	Lake area (hectares)
MS	Mean slope of watershed (%)
HW	Headwater status (yes or no)
CP	Carbonate present (yes or no)
GC	Presence of geological contact in watershed (yes or no)
PM	Lake perimeter (m)
GRN	Five category ranking of bedrock units in the Sierra Nevada (felsic, intermediate (intrusive), intermediate (extrusive), mafic/meta/carbonates, unconsolidated)
V3	Percent of watershed with nonforest vegetation

Results

Wald confidence intervals were compared to determine if random effects variance component estimates from the mixed model without covariates were significantly different from the random effects variances estimates from the model with the additional covariates included in the mean structure. For the comparison of Wald confidence intervals for all six analytes, for both pilot data sets, and for the outcomes taken at both the epilimnion and the outflow of each lake, no significant differences in random effects variance components were found between the mixed models formulated with and without covariates.

Model comparisons were also conducted using information criteria. Since the mixed models employ estimation by restricted maximum likelihood (REML), model comparison tools such as

likelihood ratio tests are invalid (Gurka 2006). Convergence under maximum likelihood (ML) was poor for these models. Recent work by Gurka (2006) indicates that certain information criteria may perform well under REML if the signal-to-noise ratio and overall variation are small. Consistent information criteria such as the consistent Akaike's Information Criterion (CAIC) and the Bayes Information Criterion (BIC) were found to perform better under REML than under ML in some simulations. Comparing AIC values between models with and without covariates for all outcomes and both pilot data sets indicated that the reduced model excluding covariates was preferable in all cases.

An examination of the fixed effects in the full model that included covariate information showed that, for most outcomes, adding the fixed temporal and spatial covariates did not produce a significant change in the mean structure. However, for the outcomes of ANC and NO₃ in the Western Lakes data set, several fixed effects were found to contribute significantly to the mean structure of the outcome. For ANC, all of the covariates were highly significant at the $\alpha = 0.10$ level. For NO₃, the covariates W ($p=0.0745$), HW ($p=0.0543$), CP ($p<0.0001$), GC ($p<0.0001$), and GRN ($p=0.0004$) were all found to be significant at the $\alpha = 0.10$ level. Similarly, the discharge mean was found to be a significant explanatory variable ($p=0.0333$) for ANC collected in the outflow of each lake. However, as discussed above, the comparison of Wald confidence intervals did not indicate any significant differences in variance component estimates between mixed models with and without the covariate data. While these covariates show evidence of significance in the mean structure, their inclusion does not impact the variance. Since the reduction of variance components was the true goal of this exercise, the lack of difference in the variance component estimates indicates no need to change power simulation inputs. However, inclusion of these covariates for future modeling of mean outcomes, especially of ANC, would certainly be justified.

Analysis Methods

To accurately estimate power to detect trend, analysis methods and tests of trend used in the trend analysis should reflect the analysis methods used in the future when data are available. The analysis approach taken here is often used for detecting trend from panel data. However, multiple methods should be used to determine if significant trends exist before management action is taken.

Parametric tests based on regression approaches and nonparametric tests such as the seasonal and regional Kendall tests and the Partial Mann-Kendall test require different assumptions and provide, in tandem, more evidence for the determination of trend. Trend in the design-based (Horvitz-Thompson) estimates of totals or means could be estimated so that the survey design is accounted for in the trend analysis. For the purposes of this report, the linear mixed model is used for trend detection in site-level measurements. Advantages of the mixed modeling approach include the ability to describe the mean structure with fixed effects and to partition the variance structure into components that influence the power to detect trend in different ways. For example, high site-to-site variation reduces power when the same sample of sites is not visited every year. However, when the [1-0] revisit design is used, the effect of the random site intercept is eliminated (Piepho and Ogutu 2002). Even small increases in year-to-year variation can greatly impact the power to detect trend (Urquhart and Kincaid 1999). When comparing power to detect trend among revisit designs, it is helpful to consider these differences.

Modeling the Trend and Variance Components

Preliminary data analysis indicated that the lake chemistry outcomes better meet model assumptions if a logarithmic transformation is applied. Modeling of the pilot data was conducted with mixed models proposed in VanLeeuwen et al. (1996) and Piepho and Ogutu (2002). Mixed models allow some effects to be considered fixed and some to be random. The fixed effects contribute to the mean of the outcome of interest and the random effects contribute to the variance. Random effects are used to estimate variation of linear trends among subjects (lakes) and over time (years). Piepho and Ogutu (2002) improve the estimator proposed by VanLeeuwen et al. (1996) in that the effect of lakes on the intercept of the linear regression may be modeled as fixed or random. If this effect is assumed random, it may also be modeled to be correlated with the random slope associated with lakes. Therefore, the mixed model approach is an extension of simple linear regression that allows a partition of the variance into components that indicate major sources of variability. The ability to modify the assumptions provides additional benefits of invariance and model flexibility. Assumptions of the mixed model approach include normally-distributed and homoscedastic error components, and modelers should check that likelihood solutions converge and produce a positive-definite Hessian matrix for reliable standard error estimates.

The mixed model proposed in both articles is:

$$y_{ijk} = \beta_0 + \beta_1 w_j + \beta_2 b_j + \beta_3 a_i + \beta_4 w_j t_i + \beta_5 c_{ij} + e_{ijk}$$

where $i=1,\dots,m_a$; $j=1,\dots,m_b$; $k=1,\dots,m$ and

m_a = the number of sites in the sample;

m_b = the number of consecutive years in the sample;

m = the number of measurements taken within a site and year;

w_j = constant representing the j^{th} year (covariate);

μ and β = fixed intercept and slope of the linear time trend;

b_j = random effect of the j^{th} year;

a_i = random intercept of i^{th} site, independent and identically distributed as $N(0, \sigma_a^2)$

t_i = random slope of i^{th} site, independent and identically distributed as $N(0, \sigma_t^2)$

c_{ij} = random effect of site by year, independent and identically distributed as $N(0, \sigma_c^2)$; and

e_{ijk} = unexplained error, independent and identically distributed as $N(0, \sigma_e^2)$

Linear mixed model approaches were used in several important papers to estimate trends in trophic lake condition (Larsen et al. 1995); water quality, physical habitat, and biological condition (Larsen et al. 2001); and chlorophyll-a (VanLeeuwen et al. 1996). Note that environmental covariates, seasonal fixed effects, and higher-order terms in time may be incorporated into the trend model.

Because this trend approach is model-based, the design probabilities are not incorporated into the trend analysis. The only complexity in the survey design other than the spatial balance is the use of variable probability sampling based on a cost surface model to reduce travel time to randomly-selected sites. Therefore, this trend analysis requires the implicit assumptions that the GRTS sample behaves similarly to a simple random sample and that the outcomes of interest are independent of the factors contributing to the cost of accessing a site. If the latter assumption is not met, then trend analysis may be best conducted within cost classes.

This analysis will examine the epilimnion and outflow means separately, so there will be no replication within a site for a particular year. The unreplicated model then excludes e_{ijk} and uses c_{ij} as the error term. While the lakes in the Seven Lakes study were not chosen randomly, the a_i term is treated as random in the mixed model so that the observed variation is considered representative of a larger population of lakes. If the lakes were chosen to be more similar or more different, then the variance among lakes will be underestimated or overestimated, respectively, in this analysis. Furthermore, the modeling approach suggested by VanLeeuwen et al. (1996) is not invariant to a shift in the origin. Piepho and Ogutu (2002) remedied this by modeling a_i and t_i jointly. The code to conduct this analysis was taken from their paper and is implemented in SAS. Because the goal of this particular analysis is to obtain estimates of random effects variance components and not to detect trend, the NOBOUND option was omitted so that nonnegative estimates of variance could be obtained.

The pilot data were examined in two different models. The first model incorporated all of the available data and used a seasonal explanatory variable. Since the lake chemistry surveys are anticipated to be conducted in August and September, the second model incorporated only the fall data and employed a covariate for month. In the case that a model did not converge, the lake effect was modeled as a fixed effect rather than a random effect. When the model did not converge for either a fixed or random lake effect, no estimates were reported. Particulate nitrogen and particulate phosphorus were available only for the epilimnion data from the Seven Lakes study. The variance component estimates that were used for the power analysis are given in Table 3. Note that these model estimates reflect analysis of each outcome on the log scale. Temporal variance components were taken from the analysis of Seven Lakes study data and estimates of spatial variance components were obtained from the analysis of data from the Western Lakes study. Preference was given to estimates of fall data only, but in the absence of viable estimates, variance components from the seasonal analysis were used.

Simulating the Population

From the model described above, estimates of the fixed effects obtained from generalized least squares and variance components obtained with REML were used to simulate similar populations with specific changes in the outcome over time. Trend was evaluated using a mixed model in the R library “lme4” (Bates 2007). The model does not account for the joint distribution of a_i and t_i . This omission causes slight overestimation of σ_a^2 and σ_t^2 in the absence of estimating σ_{at} . However, σ_{at} was very small in the SAS models and this omission should not affect power calculations.

Incorporating GRTS into the power analysis would require generating theoretical response surfaces of each analyte over space and drawing spatially-balanced samples from this surface for analysis. Since the potential of introducing error into the power analysis is increased in this approach, the GRTS membership design was not used in the power analysis. A similar problem is encountered when attempting to incorporate variable probability sampling. For these reasons, a simple random sample without replacement was used for the membership design in this power analysis.

Table 3. Power analysis inputs of fixed effects and variance components.

Analyte	$\hat{\mu}$	$\hat{\sigma}_b^2$	$\hat{\sigma}_a^2$	$\hat{\sigma}_t^2$	$\hat{\sigma}_c^2$
Spec Cond	2.0000	0.0080	0.2404	0.0005	0.0300
ANC	3.9000	0.0300	0.4000	0.0005	0.0007
NO ₃	-2.5000	0.3607	0.2614	0.0010	1.4700
SO ₄	-0.9000	0.0290	0.5400	0.0013	0.0500
PN	-4.2000	0.0457	0.0000	0.0007	0.2207
PP	-5.8000	0.1124	0.0000	0.0001	0.1670
pH	1.8988	0.0006	0.0016	0.0004	0.0008
Ca	-0.8035	0.0203	0.3985	0.0171	0.0490
Na	-1.1404	0.0364	0.3803	0.0009	0.0402
Mg	-2.7144	0.0364	0.3732	0.0337	0.0498
K	-2.0399	0.0493	0.2770	0.0039	0.0461
Cl	-2.2738	0.0567	0.1900	0.2519	0.1014
Temperature	2.9525	0.0180	0.0415	0.0414	0.0291
DON	-3.0000	0.1866	0.0000	0.0063	0.4702
PC	-2.0151	0.0925	0.0000	0.0011	0.3608
TDP	-6.0000	0.0336	1.4005	0.0020	0.9231

Calculating Power

The results of the mixed model are the fixed effects, which give the regression trend line, and the random effects which affect the variance of the response. The estimated regression slope gives the average linear change in the logged outcome over one year and this quantity must be used to evaluate the net change in the population over several years. The hypothesis of interest is whether or not the population parameter experiences a large proportional change over a given period of time. Since the regression coefficient is multiplied by the *WYear* variable that starts at zero, the intercept is actually an estimate of the initial logged population parameter at Year 0.

Let δ be the net change on the original scale to be tested. A test of population change in either direction would be formulated as:

$$H_O : |\delta| = \delta^* \text{ vs } H_A : |\delta| \neq \delta^*.$$

The mixed model of the logged response may be parameterized as in VanLeeuwen et al. (1996) and Piepho and Ogutu (2002):

$$\log y = \mu + \beta w_j + Z\gamma,$$

where μ and β represent the fixed intercept and slope, respectively, Z the random effects design matrix, and γ the random effects.

In the simulation, the logged outcomes are generated based on estimates of fixed and random effects from pilot data and assuming a stable population ($\beta=0$). Then the data are back-transformed and the population shift is applied. The population is structured to experience a net multiplicative change of δ over a period of m_b years. Therefore, for the j^{th} year of the simulation, a stable population is generated and each value is multiplied by p^{w_j} , where $p = \sqrt[m_b]{1+\delta}$.

The simulated data for the j^{th} year is obtained as:

$$\log y_j = \hat{\mu} + Z_j \hat{\gamma} .$$

The simulated data from a stable population on the original scale is:

$$y_j = \exp(\hat{\mu} + Z_j \hat{\gamma}) .$$

The simulated data experiencing a population shift is then:

$$y_j = p^{w_j} \exp(\hat{\mu} + Z_j \hat{\gamma}) .$$

To use the appropriate model in the power calculation, the response must then again be logged. Now we have:

$$\begin{aligned} \log y_j &= \log \left[p^{w_j} \exp(\hat{\mu} + Z_j \hat{\gamma}) \right] \\ &= \hat{\mu} + w_j \log p + Z_j \hat{\gamma} \end{aligned}$$

Therefore, $\beta = \log p$, where β is the mixed model slope of the log-transformed data corresponding to a population shift of δ on the original scale.

Since p has previously been defined as $p = \sqrt[m_b]{1+\delta}$, we have that

$$\beta = \log p = \log \left(\sqrt[m_b]{1+\delta} \right) = \frac{1}{m_b} \log(1+\delta) .$$

Now the test of $H_O : |\delta| = \delta^*$ vs $H_A : |\delta| \neq \delta^*$ corresponds to a test of

$$\begin{aligned} H_O : \beta &= \frac{1}{m_b} \log(1+\delta^*) \text{ or } \beta = \frac{1}{m_b} \log(1-\delta^*) \\ \text{vs} & \\ H_A : \beta &\neq \frac{1}{m_b} \log(1+\delta^*) \text{ or } \beta \neq \frac{1}{m_b} \log(1-\delta^*) \end{aligned} .$$

For the test value of $\delta^* = 0$, the test simplifies to:

$$H_O : \beta = 0 \text{ vs } H_A : \beta \neq 0$$

The test statistic is derived for the two-sided hypothesis and the rejection region is based on a t-distribution with n-2 degrees of freedom for a Type I error level of $\alpha = 0.10$.

Two approaches to determining minimum samples were initially used. The first approach examined the number of lakes needed to obtain power to detect a given change over a set period of time. The second approach examined the number of consecutive years of surveys needed to obtain power to detect a population change for a fixed sample size. Four revisit designs were examined. The values of δ represent net declines over a specified time period; these net changes correspond to annual exponential changes that are given in Table 4. For the analysis of the number of lakes needed, population changes are calculated for over period of 30 years. The plots for this initial power analysis are given in Appendix B and corresponding tables are included in Appendix C.

Table 4. Net change and corresponding annual multiplicative change.

Net change	Annual decrease		Annual increase	
	10 years	30 years	10 years	30 years
$\delta=0.20$	0.9779	0.9926	1.0184	1.0061
$\delta=0.30$	0.9650	0.9882	1.0266	1.0088
$\delta=0.40$	0.9502	0.9831	1.0342	1.0113
$\delta=0.60$	0.9124	0.9699	1.0481	1.0158
$\delta=0.80$	0.8513	0.9478	1.0605	1.0198

Populations were initially simulated with annual decreases, under the assumption that a two-sided test of trend would have the same power to detect increases and decreases in the population. However, Gerrodette (1987) stated that decreases in power are actually easier to detect than increases in populations, with the differences in power being minimal for exponential growth. Population declines were used in the preliminary analysis to compare the power to detect trend with a two-sided test for various revisit designs. Later analyses were conducted with either population increases or declines based on the monitoring goals for each specific outcome of interest. Note that, regardless of the direction of the simulated decline, all trend tests are two-sided hypothesis tests.

Based on lake chemistry work group expertise and information from the power analysis, the work group decided to adopt a [(1-0),(1-3)] revisit design and annual surveys of 25 lakes, consisting of 8 lakes in the annual panel and 17 lakes in each of the rotating revisit panels. For the index sites and the annual revisit sites, a single water sample will be taken from the epilimnion and outflow of each lake. One outflow measurement will be taken from lakes included in the rotating panels.

For the final power analysis of the [(1-0),(1-3)] revisit design for an annual sample size of 25 lakes, population increases were used to examine power for all analytes with the exception of ANC and pH, which were examined under population declines. Tables 5 and 6 provide summaries of power for the 16 analytes for a range of trends occurring over both 10- and 30-year periods. Power for the more variable analytes is examined for a larger range of net changes occurring at four levels. Reported power is that calculated for annual surveys of 25 lakes (8 in the annual panel and 17 in each of the rotating revisit panels) during the final year of surveys. Tables 7 through 22 provide power approximations for 30-year trends in tabular form; corresponding power plots are provided in Figures 2 through 17.

Table 5. Power of trend detection for 10- and 30- year trends at three levels of change.

Measure	10-year trend			30-year trend		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
Spec. Cond.	0.517	0.746	0.917	0.543	0.827	0.959
ANC*	0.304	0.481	0.734	0.479	0.808	0.968
SO ₄	0.258	0.379	0.525	0.274	0.445	0.652
PN	0.179	0.270	0.379	0.265	0.437	0.612
PP	0.158	0.239	0.234	0.218	0.330	0.441
pH	1.000	1.000	1.000	0.921	1.000	1.000
Na*	0.241	0.332	0.414	0.283	0.469	0.682

*Indicates that population decline was simulated for power calculations.

Table 6. Power of trend detection for 10- and 30- year trends at four levels of change.

Measure	10-year trend				30-year trend			
	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
NO ₃	0.152	0.161	0.212	0.244	0.138	0.192	0.307	0.403
Ca	0.210	0.407	0.645	0.788	0.131	0.169	0.281	0.341
Mg	0.168	0.293	0.485	0.596	0.118	0.140	0.198	0.231
K	0.228	0.382	0.539	0.705	0.178	0.317	0.571	0.729
Cl	0.104	0.125	0.182	0.240	0.105	0.115	0.120	0.112
Temp.	0.150	0.326	0.523	0.639	0.122	0.133	0.180	0.199
DON	0.145	0.202	0.269	0.312	0.112	0.194	0.318	0.419
PC	0.180	0.268	0.346	0.497	0.196	0.395	0.629	0.777
TDP	0.166	0.304	0.462	0.594	0.192	0.402	0.630	0.795

Table 7. Fall specific conductance power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.202	0.203	0.223
10	0.163	0.215	0.283
15	0.236	0.364	0.524
20	0.324	0.575	0.780
25	0.474	0.728	0.902
30	0.543	0.827	0.959

Table 8. Fall ANC power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=-0.20$	$\delta=-0.30$	$\delta=-0.40$
5	0.183	0.182	0.200
10	0.131	0.152	0.207
15	0.165	0.260	0.435
20	0.243	0.466	0.688
25	0.366	0.668	0.913
30	0.479	0.808	0.968

Table 9. Fall NO₃ power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.175	0.168	0.185	0.163
10	0.116	0.123	0.130	0.133
15	0.121	0.117	0.117	0.140
20	0.109	0.123	0.157	0.184
25	0.115	0.178	0.217	0.288
30	0.138	0.192	0.307	0.403

Table 10. Fall SO₄ power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.198	0.200	0.218
10	0.142	0.145	0.166
15	0.137	0.181	0.245
20	0.167	0.281	0.399
25	0.221	0.369	0.521
30	0.274	0.445	0.652

Table 11. Fall PN power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.180	0.169	0.167
10	0.127	0.141	0.160
15	0.143	0.165	0.207
20	0.163	0.195	0.312
25	0.200	0.308	0.442
30	0.265	0.437	0.612

Table 12. Fall PP power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.189	0.189	0.181
10	0.124	0.129	0.138
15	0.134	0.143	0.162
20	0.139	0.175	0.188
25	0.153	0.224	0.299
30	0.218	0.330	0.441

Table 13. Fall pH power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.296	0.433	0.631
10	0.642	0.948	0.999
15	0.830	0.999	1.000
20	0.907	0.997	1.000
25	0.937	1.000	1.000
30	0.921	1.000	1.000

Table 14. Fall Ca power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.143	0.152	0.178	0.179
10	0.102	0.136	0.170	0.192
15	0.114	0.125	0.228	0.289
20	0.098	0.180	0.233	0.319
25	0.098	0.169	0.257	0.334
30	0.131	0.169	0.281	0.341

Table 15. Fall Na power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=-0.20$	$\delta=-0.30$	$\delta=-0.40$
5	0.197	0.203	0.226
10	0.134	0.153	0.168
15	0.132	0.169	0.232
20	0.162	0.262	0.374
25	0.231	0.368	0.518
30	0.283	0.469	0.682

Table 16. Fall Mg power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.142	0.148	0.171	0.167
10	0.097	0.114	0.136	0.146
15	0.109	0.103	0.170	0.206
20	0.091	0.141	0.168	0.218
25	0.078	0.133	0.182	0.238
30	0.118	0.140	0.198	0.231

Table 17. Fall K power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.191	0.195	0.217	0.205
10	0.128	0.139	0.165	0.192
15	0.116	0.175	0.251	0.351
20	0.105	0.236	0.387	0.511
25	0.135	0.315	0.476	0.649
30	0.178	0.317	0.571	0.729

Table 18. Fall Cl power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.104	0.117	0.143	0.137
10	0.088	0.102	0.099	0.088
15	0.096	0.081	0.117	0.119
20	0.076	0.100	0.110	0.111
25	0.080	0.107	0.096	0.112
30	0.105	0.115	0.120	0.112

Table 19. Fall temperature power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.118	0.132	0.165	0.152
10	0.092	0.109	0.144	0.169
15	0.113	0.097	0.171	0.196
20	0.091	0.138	0.157	0.197
25	0.081	0.128	0.159	0.210
30	0.122	0.133	0.180	0.199

Table 20. Fall DON power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.193	0.171	0.182	0.170
10	0.122	0.130	0.140	0.136
15	0.132	0.133	0.145	0.160
20	0.113	0.132	0.203	0.244
25	0.102	0.174	0.239	0.340
30	0.112	0.194	0.318	0.419

Table 21. Fall PC power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.186	0.171	0.171	0.166
10	0.121	0.139	0.158	0.154
15	0.138	0.159	0.211	0.232
20	0.132	0.183	0.319	0.408
25	0.139	0.283	0.452	0.614
30	0.196	0.395	0.629	0.777

Table 22. Fall TDP power, 25 lakes, [(1-0),(2-3)] revisit design.

Years	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.120	0.116	0.117	0.119
10	0.102	0.124	0.139	0.170
15	0.119	0.166	0.244	0.321
20	0.137	0.239	0.355	0.470
25	0.156	0.306	0.496	0.668
30	0.192	0.402	0.630	0.795

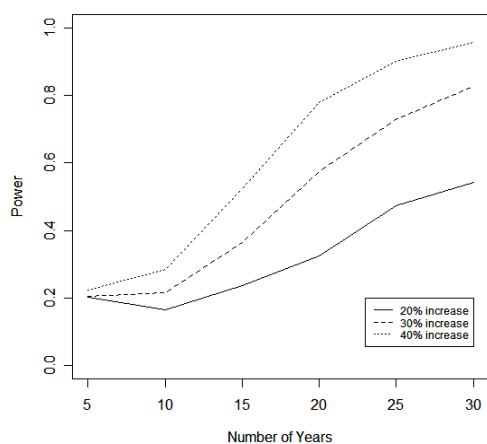


Figure 2. Power of trend detection for changes in fall specific conductance for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

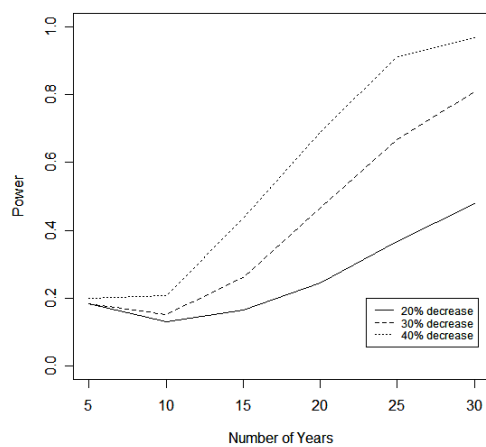


Figure 3. Power of trend detection for changes in fall ANC for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

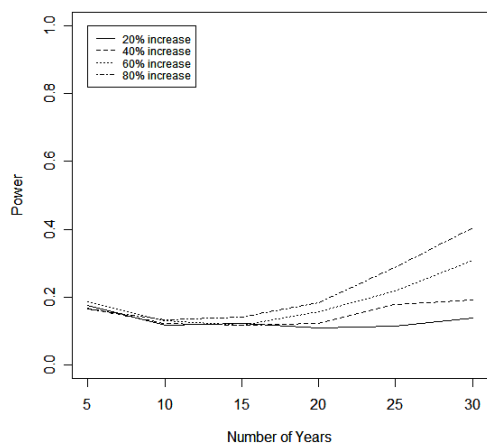


Figure 4. Power of trend detection for changes in fall NO₃ for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

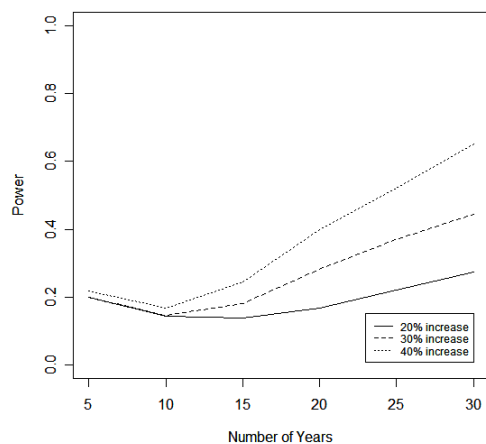


Figure 5. Power of trend detection for changes in fall SO₄ for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

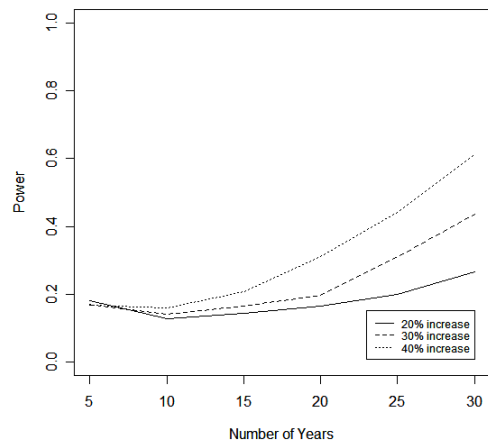


Figure 6. Power of trend detection for changes in fall PN for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

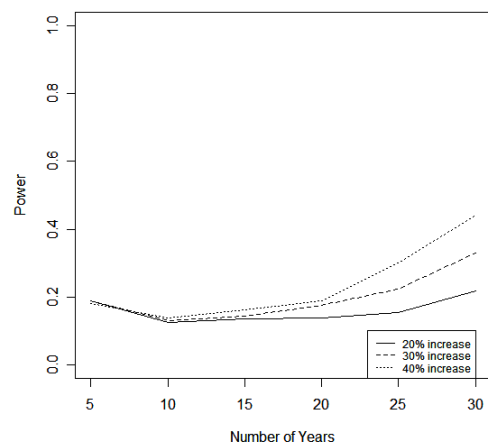


Figure 7. Power of trend detection for changes in fall PP for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

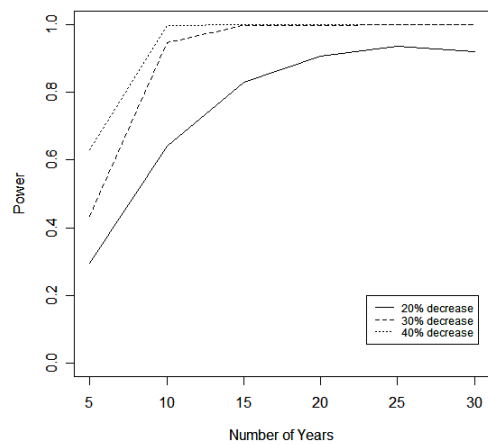


Figure 8. Power of trend detection for changes in fall pH for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

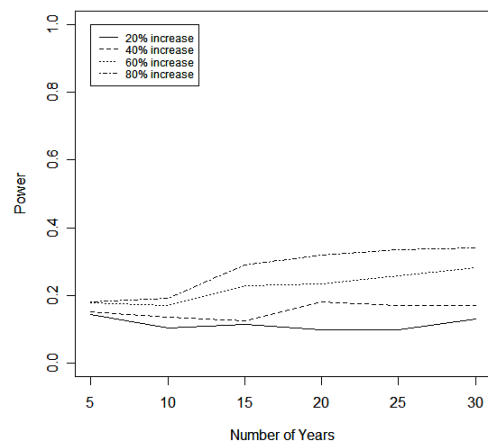


Figure 9. Power of trend detection for changes in fall Ca for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

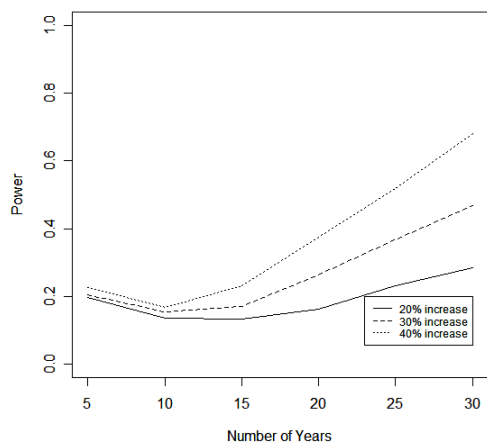


Figure 10. Power of trend detection for changes in fall Na for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

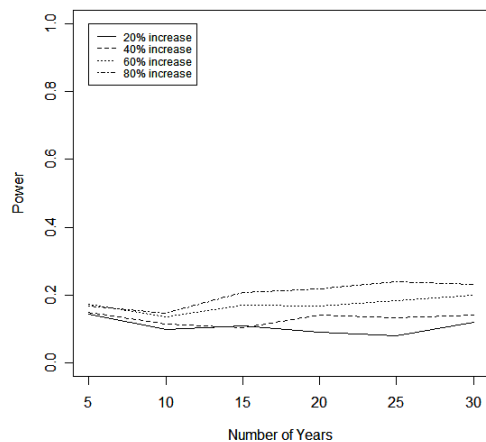


Figure 11. Power of trend detection for changes in fall Mg for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

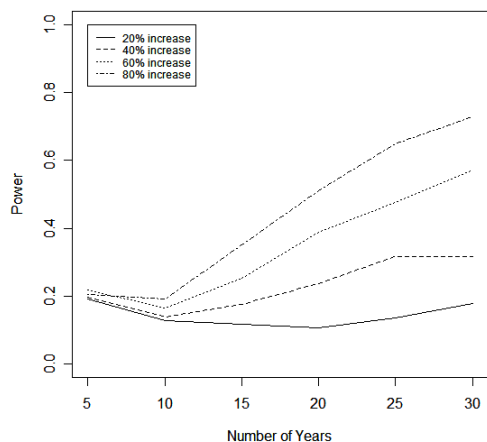


Figure 12. Power of trend detection for changes in fall K for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

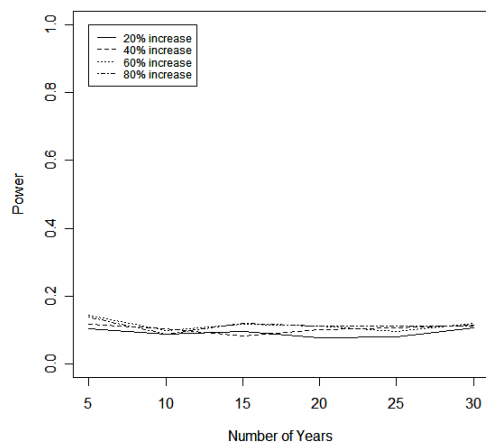


Figure 13. Power of trend detection for changes in fall Cl for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

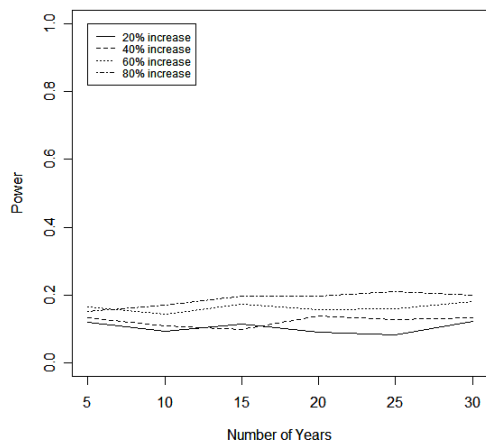


Figure 14. Power of trend detection for changes in fall temperature for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

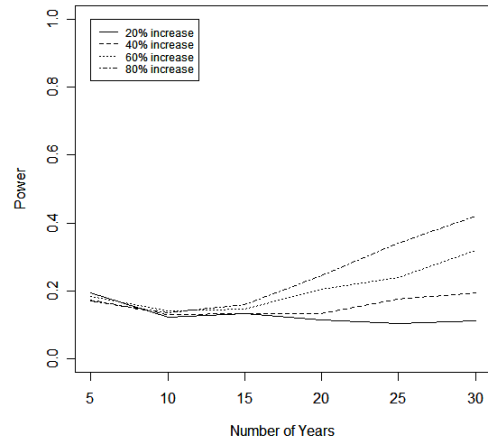


Figure 15. Power of trend detection for changes in fall DON for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

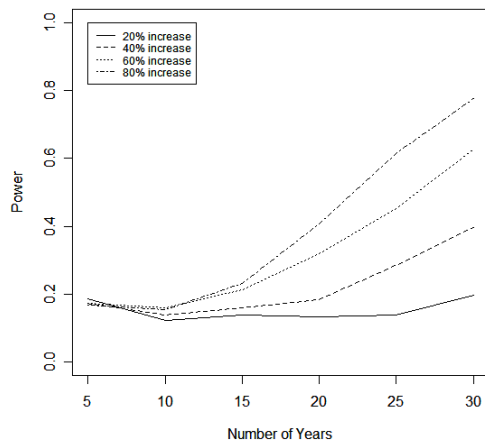


Figure 16. Power of trend detection for changes in fall PC for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

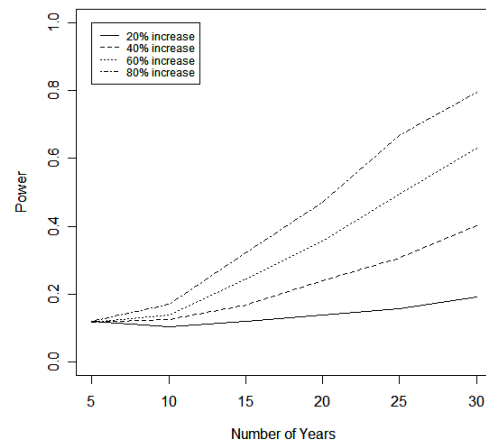


Figure 17. Power of trend detection for changes in fall TDP for annual surveys of 25 lakes; revisit = [(1-0),(1-3)].

Discussion

The results of the power analysis indicate that the sixteen analytes examined exhibit a range of variation that affects the ability to detect trend over time. Power is calculated as a function of the number of lakes visited or the number of consecutive years for which the survey is conducted. As evidenced by the power plots in Appendix B, increasing the number of lakes often does not increase the power substantially. More important to the ability to detect trend is the consistent continuation of surveys over time. Current power analyses are based on annual surveys of SIEN lakes; less frequent surveys will reduce the power to detect long-term changes in the population. This commitment to long-term monitoring is integral to the success of lake chemistry monitoring.

In some cases, the [1-0] revisit appears to have slightly lower power to detect trend than some of the other revisit designs examined which contradicts some of the previous research on the power of revisit designs (Urquhart and Kincaid 1999). For analytes with high site-to-site variance, it is reasonable that a revisit design that incorporates more lakes within the sample would have advantages to estimating trend. Another factor that may contribute to this discrepancy is how the annual revisit panel was used in the simulation. For sample sizes that did not allocate equally across panels for a given revisit design, the “extra” lakes were placed in the annual revisit panel so that the desired sample size could be obtained and the non-annual panels could be balanced. Therefore the annual panel size differs among revisit designs and may slightly confound comparisons between revisit designs.

For most of the analytes and scenarios examined, the revisit design appears to have little impact on power. The revisit design should be chosen so that the complete set of sites is visited in as few years as possible but so that revisits accommodate dual monitoring goals of status and trend estimation. Annual status estimates benefit from increased sample size within a given year. Consistent sampling over time improves trend estimates. Drawbacks of visiting one park per year include longer required intervals for attaining adequate power to detect trend and potential confounding of park and year. When the power to test status estimates is examined, SIEN personnel may determine if sampling resources need to be reallocated to optimize the dual goals of status and trend monitoring.

Often the ability to detect trend is reliant on the magnitude of the trend itself. For an analyte such as NO_3 , with a low-signal-to-noise ratio, only the most extreme trends can be detected. When the time frame of interest was expanded to 100 years, the tests of trend for NO_3 still exhibited low power. The high amount of variation in this analyte will make trend detection difficult unless dramatic changes are occurring. Standardizing the response design by taking measurements at similar times of day or year and using labs with low detection limits may help to reduce noise in the outcomes of interest. Given the high cost of accessing sites (up to five days with a heavy pack), the cost of monitoring additional analytes is thought worthwhile by SIEN personnel. Additional lab costs are not prohibitively high compared to the cost of missing a dramatic trend simply because an analyte exhibits low power for detecting less severe trends.

Power was most acceptable for specific conductance and pH, moderate for several analytes, and low for several analytes. Low power is often a product of high year-to-year variation. Even small increases in this variance component can impact power to detect trend greatly (Urquhart and

Kincaid 1999). Estimated year-to-year variation might be reduced in two ways (Urquhart et al. 1998). First, covariates may be incorporated in the trend model to explain annual variability. In the pilot data sets, the available covariates were not useful in explaining variability. Second, trend may be estimated within subpopulations that exhibit similar variance structures. Identifying these subpopulations also requires the collection of appropriate covariate information. However, identification of subpopulations post-hoc may be preferable over targeting only specific subpopulations in the design phase so that the scope of inference is not limited to a smaller range of SIEN lakes.

When three years of monitoring data are available, prospective power to detect trend will be reevaluated. Then the dual goals of status and trend monitoring may be assessed. The power simulation provides power approximations as a function of sample size so that adequate sample sizes may be determined. Other approaches, especially those that are less labor-intensive will be examined as well.

Examination of the power to detect trend provides considerable information in the survey planning stage. Realistic goals may be set when the variable nature of an outcome of interest is understood. The survey design, the revisit design, nonsampling error, analysis approaches, and many sources of variation all affect the ability to accurately measure trend over time. Efforts to incorporate as many of these issues as possible into the monitoring protocol will contribute to the success of this long-term monitoring project.

Literature Cited

- Bates, D. 2007. The lme4 package. Available at <http://cran.r-project.org/> (accessed 2007).
- Clow, D. W., R. G. Striegl, M. Nanus, M. A. Mast, D. H. Campbell, and D. P. Krabbenhoft. 2002. Chemistry of selected high-elevation lakes in seven national parks in the western United States. *Water Air and Soil Pollution* 2:139–164.
- Eilers, J. M., D. F. Brakke, D. H. Landers, and W. S. Overton. 1989. Chemistry of wilderness lakes in the Western United States. *Environmental Monitoring and Assessment* 12:3-21.
- Gallegos, A. and N. Berg. 2007. Western lakes survey and watershed characterization data. U.S. Forest Service, Sierra National Forest. Unpublished data set.
- Gerrodette, T. 1987. A power analysis for detecting trends. *Ecology* 68:1364–1372.
- Gleit, A. 1985. Estimation for small normal data sets with detection limits. *Environmental Science and Technology* 19:1206-1213.
- Gurka, M. J. 2006. Selecting the best linear mixed model under REML. *The American Statistician* 60:19–26.
- Helsel, D. R. 2005. *Nondetects and data analysis*. John Wiley and Sons, Inc., New Jersey.
- Kincaid, T. 2006. User Guide for spsurvey, Version 1.4 - Probability survey design and analysis functions. Available at <http://cran.r-project.org/> (accessed 2007).
- Larsen, D. P., T. M. Kincaid, S. E. Jacobs, and N. S. Urquhart. 2001. Designs for evaluating local and regional scale trends. *BioScience* 51(12):1069-1078.
- Larsen, D. P., N. S. Urquhart, and D. L. Kugler. 1995. Regional scale trend monitoring of indicators of trophic condition of lakes. *Water Resources Bulletin* 31:117-140.
- Lessler, J. T. and W. D. Kalsbeek 1992. *Nonsampling error in surveys*. John Wiley and Sons, Inc., New York.
- McDonald, T. L. 2003. Review of environmental monitoring methods: Survey designs. *Environmental Monitoring and Assessment* 85:277–292.
- Melack, J., J. O. Sickman, A. Leydecker, and D. Marrett. 1998. Comparative analyses of high-altitude lakes and catchments in the Sierra Nevada susceptibility to acidification. Final report to the California Air Resources Board, Contract No. A032-188., Sacramento, California.
- Oh, H. L. and F. J. Scheuren. 1983. Weighting adjustment for unit non-response. In W. G. Madow, I. Olkin, and D. B. Rubin, editors. *Incomplete data in sample surveys*, Vol. 2 (pp. 143–184). Academic Press, New York.
- Piepho, H. P. and J. O. Ogutu. 2002. A simple mixed model for trend analysis in wildlife populations. *Journal of Agricultural, Biological, and Environmental Statistics* 7:350–360.

- SAS Institute, Inc. 2004. SAS 9.1.3 Help and documentation. SAS Institute Inc., Cary, North Carolina.
- Shumway, R. H., R. S. Azari, and M. Kayhanian. 2002. Statistical approaches to estimating mean water quality concentrations with detection limits. *Environmental Science and Technology* 36:3345-3353.
- Stevens, D. L. and A. R. Olsen. 2003. Variance estimation for spatially balanced samples of environmental resources. *Environmetrics* 14:593–610.
- Urquhart, N. S. and T. M. Kincaid. 1999. Designs for detecting trend from repeated surveys of ecological resources. *Journal of Agricultural, Biological, and Environmental Statistics* 4(4):404–414.
- Urquhart, N. S., S. G. Paulsen, and D. P. Larsen. 1998. Monitoring for policy-relevant regional trends over time. *Ecological Applications* 8(2):246-257.
- Urquhart, N. S., W. S. Overton, and D. S. Birkes. 1993. Comparing sampling designs for monitoring ecological status and trends: impact of temporal patterns. *In* V. Barnett and K. F. Turkman, editors. *Statistics for the environment*. John Wiley and Sons Ltd.
- VanLeeuwen, D. M., L. W. Murray, and N. S. Urquhart. 1996. A mixed model with both fixed and random trend components across time. *Journal of Agricultural, Biological, and Environmental Statistics* 1(4):435–453.

Appendix A: Comparison of Power Plots for Uncensored Data and for Data that Were Left-Censored and Adjusted by Multiple Imputation

Figures

	Page
Figure A1: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0).....	35
Figure A2: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0), MDL adjustment	35
Figure A3: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,2-3)	35
Figure A4: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,2-3), MDL adjustment	35
Figure A7: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0)	36
Figure A8: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0), MDL adjustment	36
Figure A9: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3).....	36
Figure A10: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3), MDL adjustment	36
Figure A11: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3)	36
Figure A12: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3), MDL adjustment	36
Figure A13: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0)	37
Figure A14: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0), MDL adjustment	37
Figure A15: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-3).....	37

Figures (continued)

Page

Figure A16: Power of trend detection for changes in fall PP for annual surveys for
30 lakes; revisit = (1-0,2-3), MDL adjustment 37

Figure A17: Power of trend detection for changes in fall PP for annual surveys for
30 lakes; revisit = (1-0,1-3).....37

Figure A18: Power of trend detection for changes in fall PP for annual surveys for
30 lakes; revisit = (1-0,1-3), MDL adjustment 37

Figure A1: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0)

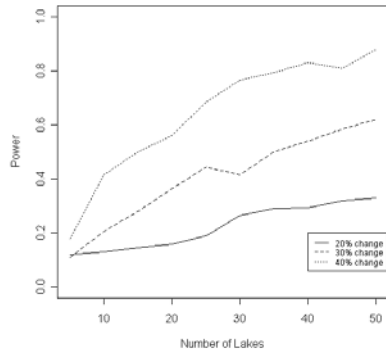


Figure A2: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0), MDL adjustment

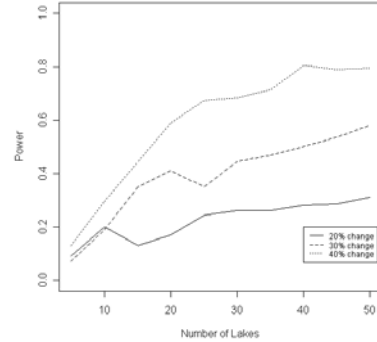


Figure A3: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,2-3)

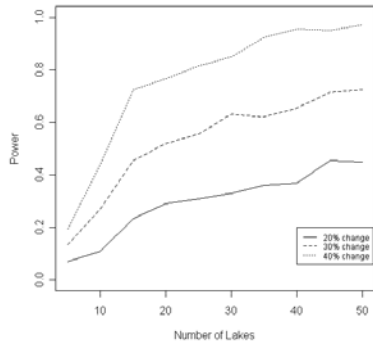


Figure A4: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,2-3), MDL adjustment

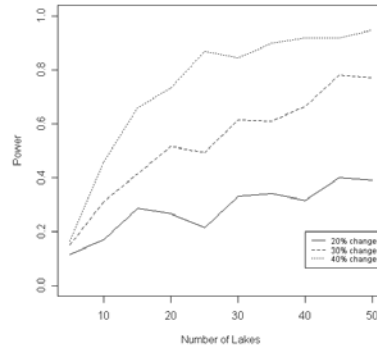


Figure A5: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,1-3)

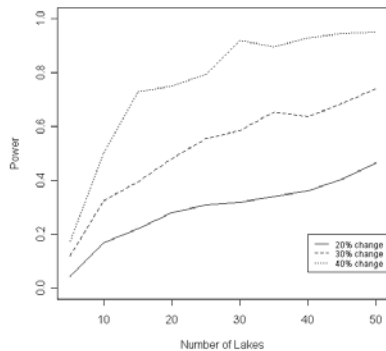


Figure A6: Power of trend detection for changes in fall SO4 for annual surveys over 30 years; revisit = (1-0,1-3), MDL adjustment

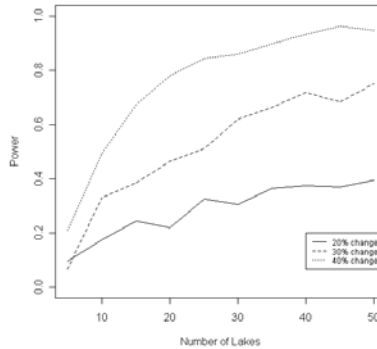


Figure A7: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0)

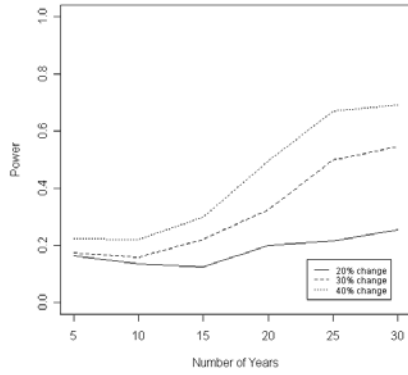


Figure A8: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0), MDL adjustment

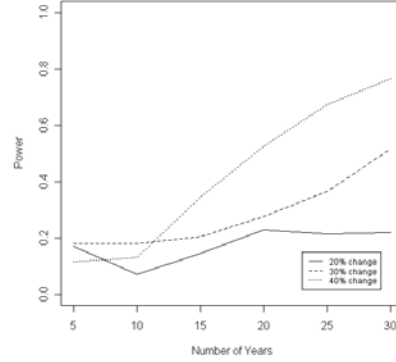


Figure A9: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3)

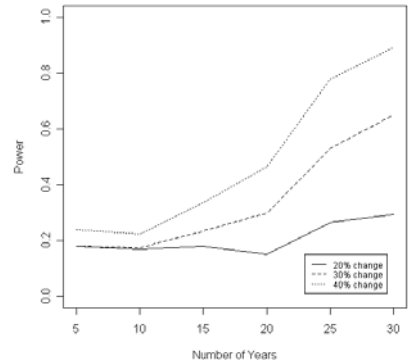


Figure A10: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3), MDL adjustment

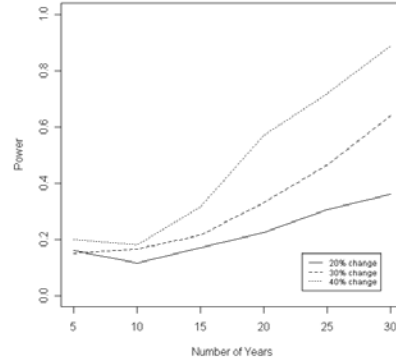


Figure A11: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3)

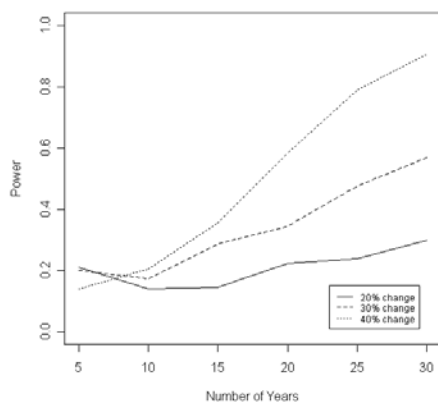


Figure A12: Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3), MDL adjustment

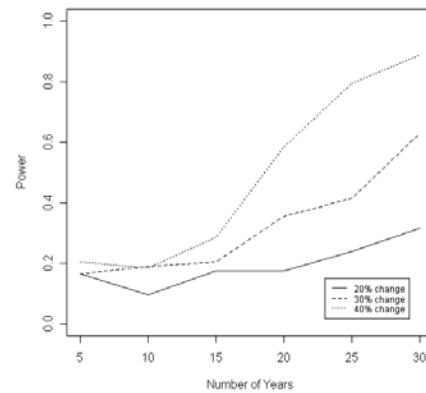


Figure A13: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0)

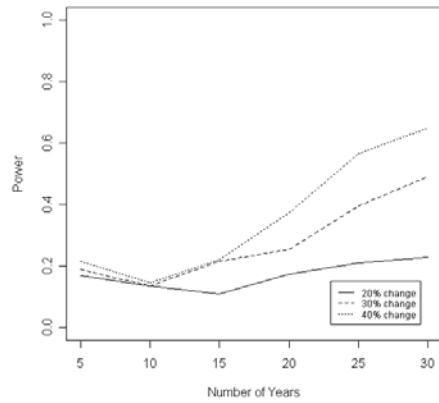


Figure A14: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0), MDL adjustment

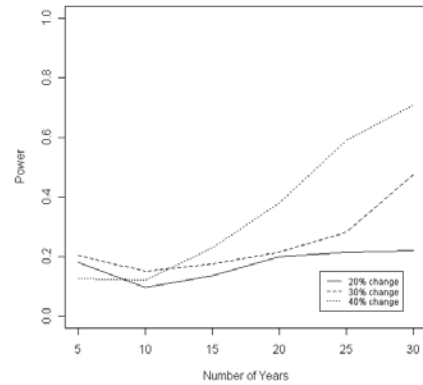


Figure A15: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-3)

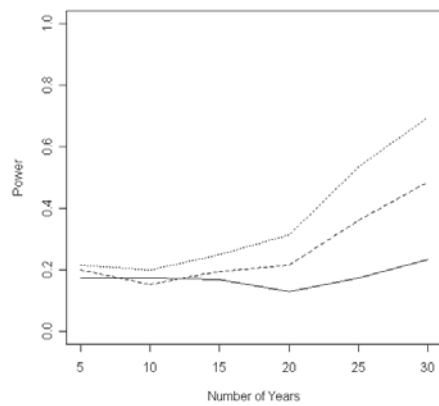


Figure A16: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-3), MDL adjustment

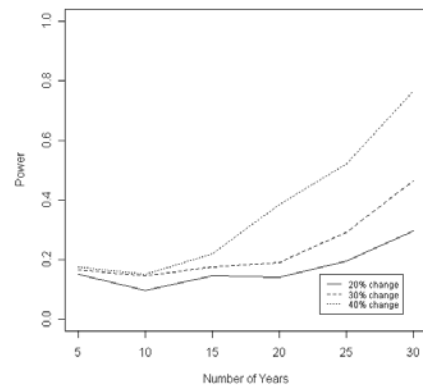


Figure A17: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,1-3)

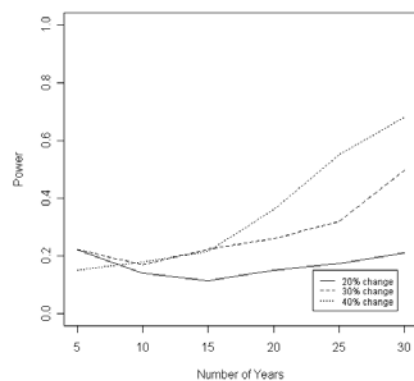
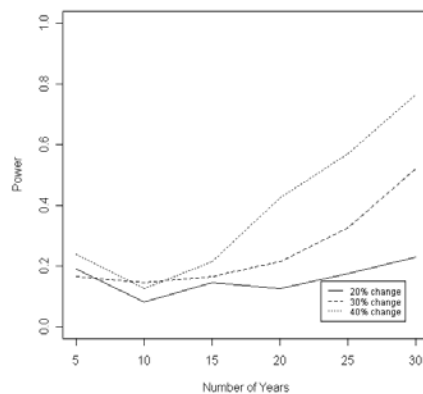


Figure A18: Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,1-3), MDL adjustment



Appendix B: Power Plots for Six Analytes and Four Revisit Designs

Note: All simulated population changes are declines.

Figures

	Page
Figure B1. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0).....	46
Figure B2. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,2-3).	46
Figure B3. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,1-3).	46
Figure B4. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,2-5).	46
Figure B5. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0).....	47
Figure B6. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,2-3).	47
Figure B7. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,1-3).	47
Figure B8. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,2-5).	47
Figure B9. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0).	48
Figure B10. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,2-3).	48
Figure B11. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,1-3).	48
Figure B12. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,2-5).	48
Figure B13. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0).	49

Figures (continued)

	Page
Figure B14. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,2-3).	49
Figure B15. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,1-3).	49
Figure B16. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,2-5).	49
Figure B17. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0).	50
Figure B18. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,2-3).	50
Figure B19. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,1-3).	50
Figure B20. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,2-5).	50
Figure B21. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0).	51
Figure B22. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,2-3).	51
Figure B23. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,1-3).	51
Figure B24. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,2-5).	51
Figure B25. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0).	52
Figure B26. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,2-3).	52
Figure B27. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,1-3).	52
Figure B28. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,2-5).	52

Figures (continued)

	Page
Figure B29. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0).	53
Figure B30. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,2-3).	53
Figure B31. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,1-3).	53
Figure B32. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,2-5).	53
Figure B33. Power of trend detection for changes in fall NO ₃ for annual surveys over 10 years; revisit = (1-0).	54
Figure B34. Power of trend detection for changes in fall NO ₃ for annual surveys over 10 years; revisit = (1-0,2-3).	54
Figure B35. Power of trend detection for changes in fall NO ₃ for annual surveys over 10 years; revisit = (1-0,1-3).	54
Figure B36. Power of trend detection for changes in fall NO ₃ for annual surveys over 10 years; revisit = (1-0,2-5).	54
Figure B37. Power of trend detection for changes in fall NO ₃ for annual surveys over 30 years; revisit = (1-0).	55
Figure B38. Power of trend detection for changes in fall NO ₃ for annual surveys over 30 years; revisit = (1-0,2-3).	55
Figure B39. Power of trend detection for changes in fall NO ₃ for annual surveys over 30 years; revisit = (1-0,1-3).	55
Figure B40. Power of trend detection for changes in fall NO ₃ for annual surveys over 30 years; revisit = (1-0,2-5).	55
Figure B41. Power of trend detection for changes in fall NO ₃ for annual surveys for 25 lakes; revisit = (1-0).	56
Figure B42. Power of trend detection for changes in fall NO ₃ for annual surveys for 25 lakes; revisit = (1-0,2-3).	56
Figure B43. Power of trend detection for changes in fall NO ₃ for annual surveys for 25 lakes; revisit = (1-0,1-3).	56

Figures (continued)

	Page
Figure B44. Power of trend detection for changes in fall NO ₃ for annual surveys for 25 lakes; revisit = (1-0,2-5).	56
Figure B45. Power of trend detection for changes in fall NO ₃ for annual surveys for 30 lakes; revisit = (1-0).	57
Figure B46. Power of trend detection for changes in fall NO ₃ for annual surveys for 30 lakes; revisit = (1-0,2-3).	57
Figure B47. Power of trend detection for changes in fall NO ₃ for annual surveys for 30 lakes; revisit = (1-0,1-3).	57
Figure B48. Power of trend detection for changes in fall NO ₃ for annual surveys for 30 lakes; revisit = (1-0,2-5).	57
Figure B49. Power of trend detection for changes in fall SO ₄ for annual surveys over 10 years; revisit = (1-0).	58
Figure B50. Power of trend detection for changes in fall SO ₄ for annual surveys over 10 years; revisit = (1-0,2-3).	58
Figure B51. Power of trend detection for changes in fall SO ₄ for annual surveys over 10 years; revisit = (1-0,1-3).	58
Figure B52. Power of trend detection for changes in fall SO ₄ for annual surveys over 10 years; revisit = (1-0,2-5).	58
Figure B53. Power of trend detection for changes in fall SO ₄ for annual surveys over 30 years; revisit = (1-0).	59
Figure B54. Power of trend detection for changes in fall SO ₄ for annual surveys over 30 years; revisit = (1-0,2-3).	59
Figure B55. Power of trend detection for changes in fall SO ₄ for annual surveys over 30 years; revisit = (1-0,1-3).	59
Figure B56. Power of trend detection for changes in fall SO ₄ for annual surveys over 30 years; revisit = (1-0,2-5).	59
Figure B57. Power of trend detection for changes in fall SO ₄ for annual surveys for 25 lakes; revisit = (1-0).	60
Figure B58. Power of trend detection for changes in fall SO ₄ for annual surveys for 25 lakes; revisit = (1-0,2-3).	60

Figures (continued)

	Page
Figure B59. Power of trend detection for changes in fall SO ₄ for annual surveys for 25 lakes; revisit = (1-0,1-3).	60
Figure B60. Power of trend detection for changes in fall SO ₄ for annual surveys for 25 lakes; revisit = (1-0,2-5).	60
Figure B61. Power of trend detection for changes in fall SO ₄ for annual surveys for 30 lakes; revisit = (1-0).	61
Figure B62. Power of trend detection for changes in fall SO ₄ for annual surveys for 30 lakes; revisit = (1-0,2-3).	61
Figure B63. Power of trend detection for changes in fall SO ₄ for annual surveys for 30 lakes; revisit = (1-0,1-3).	61
Figure B64. Power of trend detection for changes in fall SO ₄ for annual surveys for 30 lakes; revisit = (1-0,2-5).	61
Figure B65. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0).	62
Figure B66. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,2-3).	62
Figure B67. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,1-3).	62
Figure B68. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,2-5).	62
Figure B69. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0).	63
Figure B70. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,2-3).	63
Figure B71. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,1-3).	63
Figure B72. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,2-5).	63
Figure B73. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0).	64

Figures (continued)

	Page
Figure B74. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,2-3).....	64
Figure B75. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,1-3).....	64
Figure B76. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,2-5).....	64
Figure B77. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0).....	65
Figure B78. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3).....	65
Figure B79. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3).....	65
Figure B80. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-5).....	65
Figure B81. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0).....	66
Figure B82. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,2-3).	66
Figure B83. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,1-3).	66
Figure B84. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,2-5).	66
Figure B85. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0).....	67
Figure B86. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0,2-3).	67
Figure B88. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0,2-5).	67
Figure B89. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0).	68

Figures (continued)

	Page
Figure B90. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,2-3).....	68
Figure B91. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,1-3).....	68
Figure B92. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,2-5).....	68
Figure B93. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0).....	69
Figure B94. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-3).....	69
Figure B95. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,1-3).....	69
Figure B96. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-5).....	69

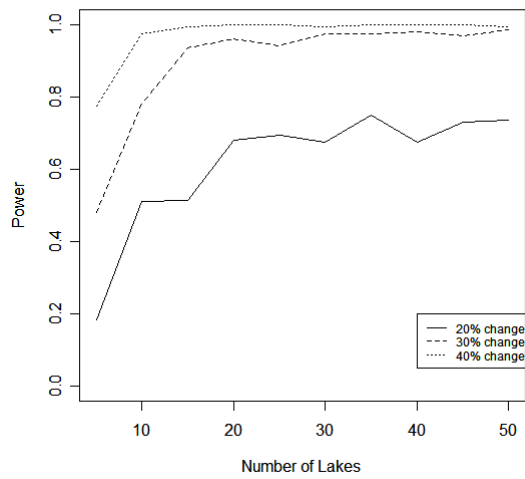


Figure B1. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0).

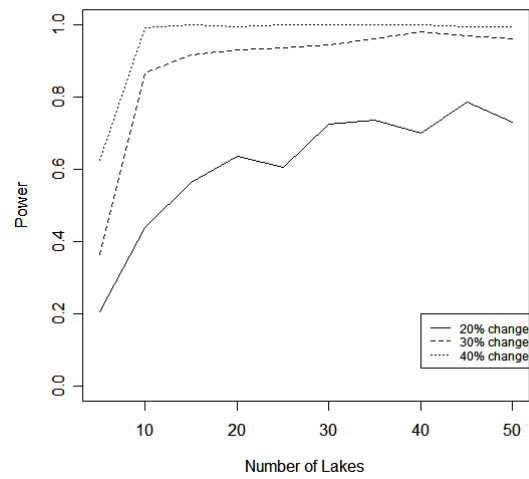


Figure B2. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,2-3).

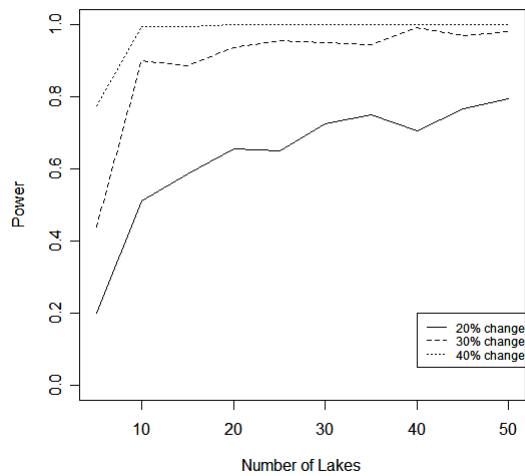


Figure B3. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,1-3).

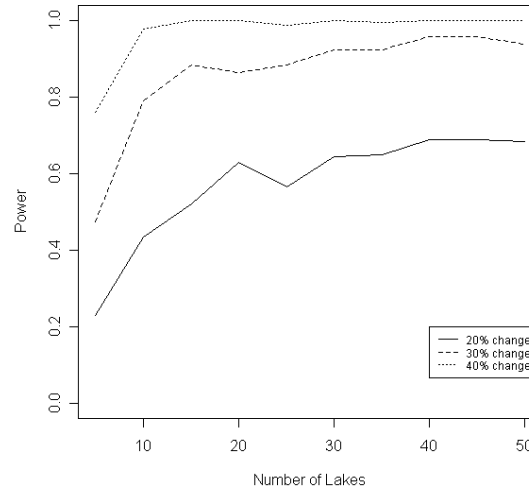


Figure B4. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years; revisit = (1-0,2-5).

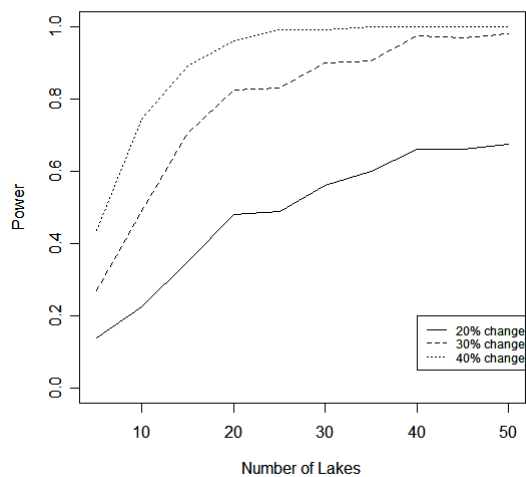


Figure B5. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0).

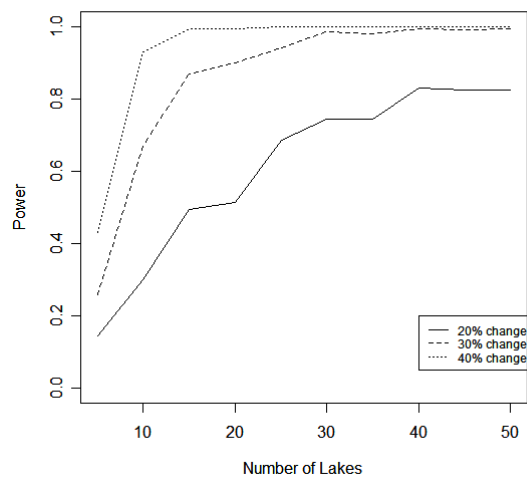


Figure B6. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,2-3).

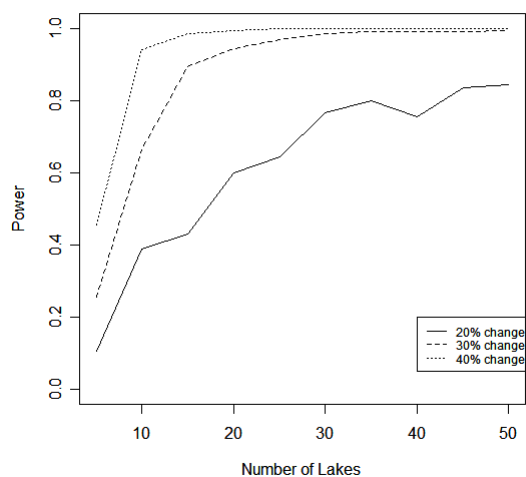


Figure B7. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,1-3).

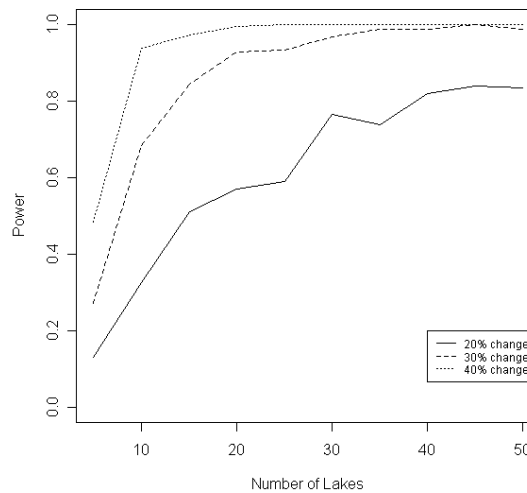


Figure B8. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years; revisit = (1-0,2-5).

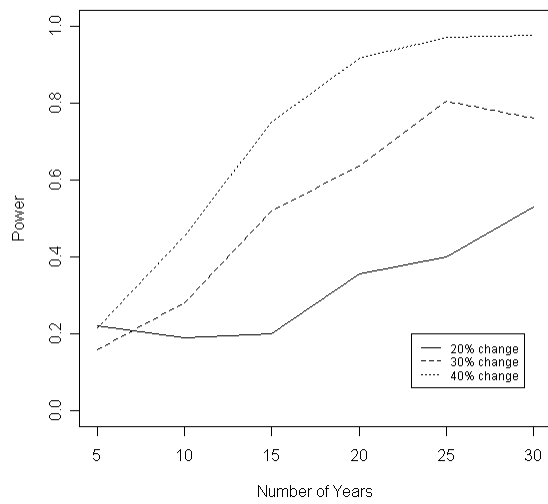


Figure B9. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0).

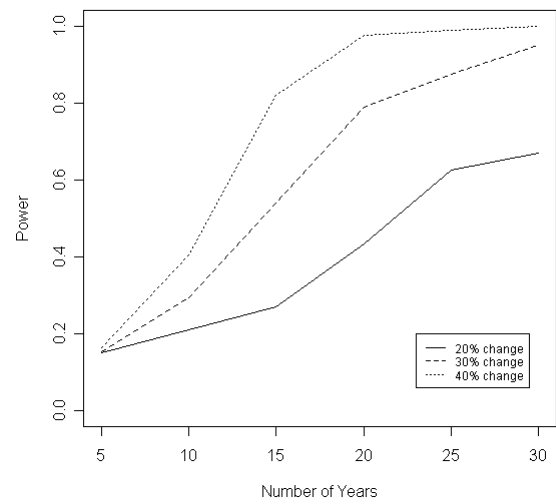


Figure B10. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,2-3).

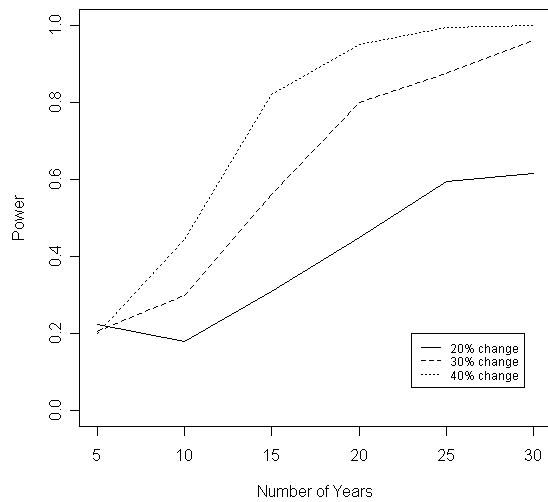


Figure B11. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,1-3).

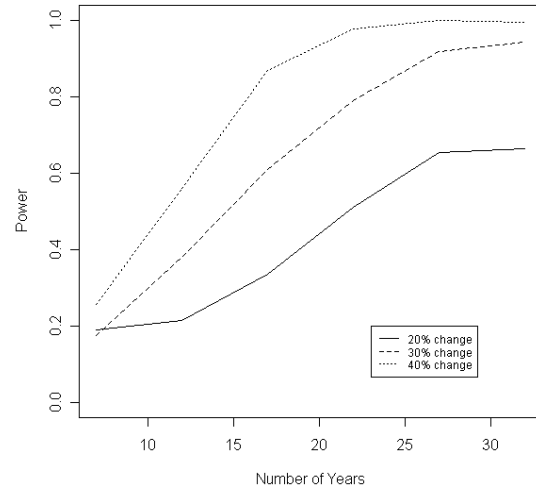


Figure B12. Power of trend detection for changes in fall specific conductance for annual surveys for 25 lakes; revisit = (1-0,2-5).

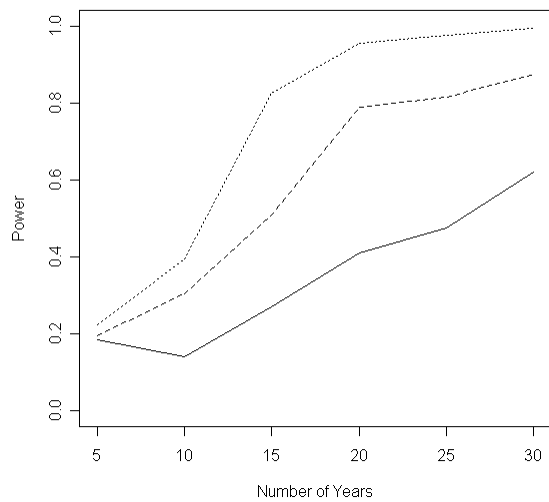


Figure B13. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0).

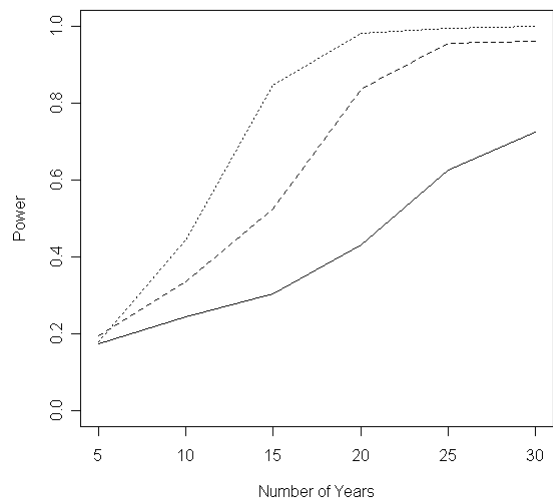


Figure B14. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,2-3).

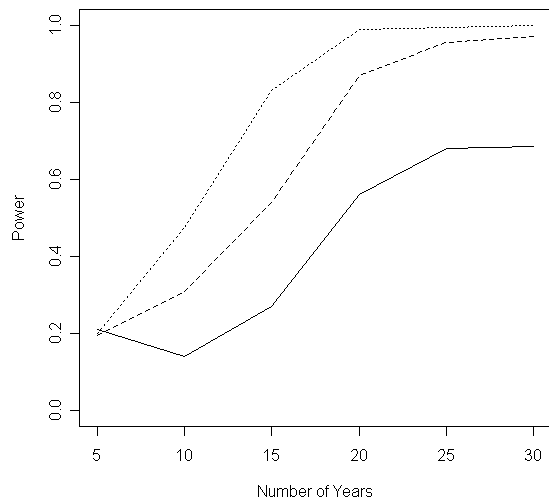


Figure B15. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,1-3).

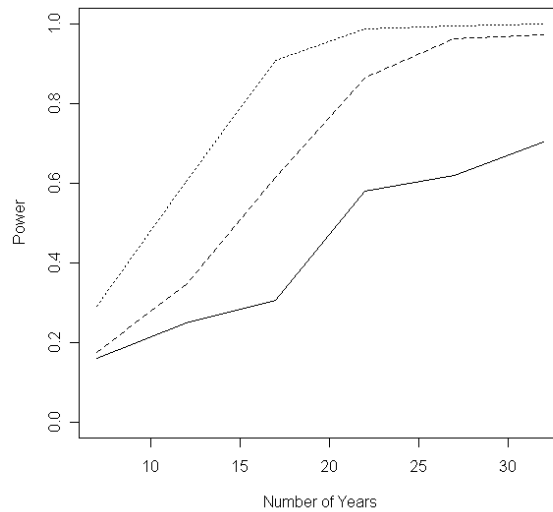


Figure B16. Power of trend detection for changes in fall specific conductance for annual surveys for 30 lakes; revisit = (1-0,2-5).

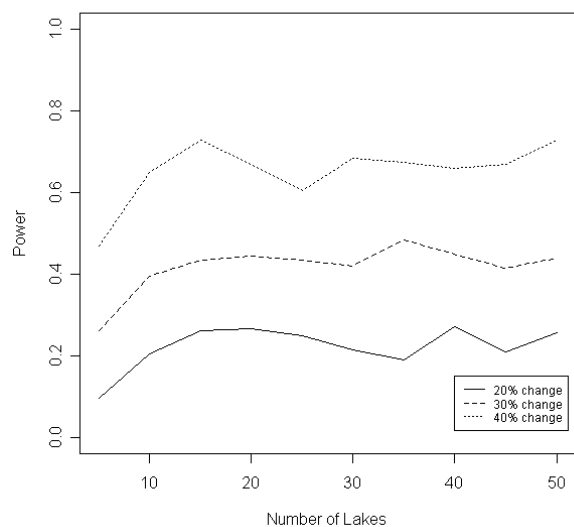


Figure B17. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0).

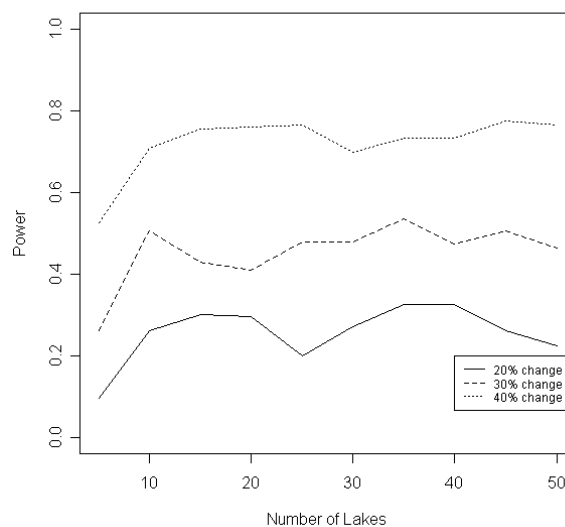


Figure B18. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,2-3).

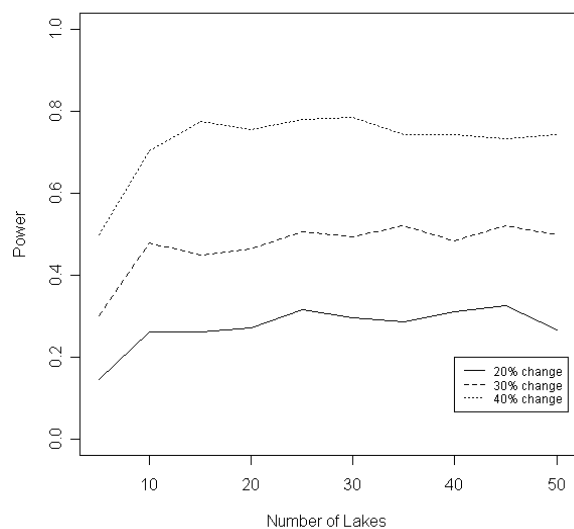


Figure B19. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,1-3).

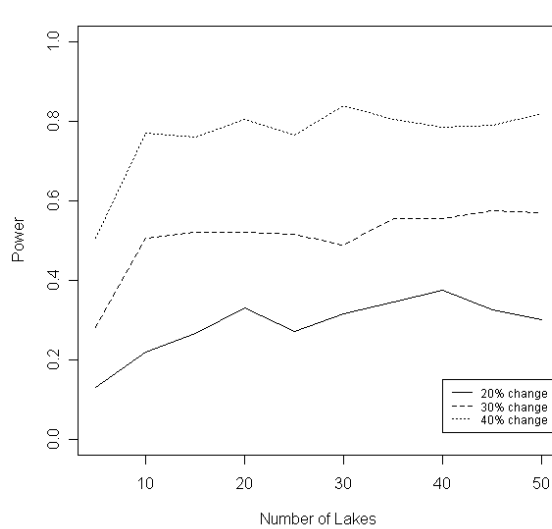


Figure B20. Power of trend detection for changes in fall ANC for annual surveys over 10 years; revisit = (1-0,2-5).

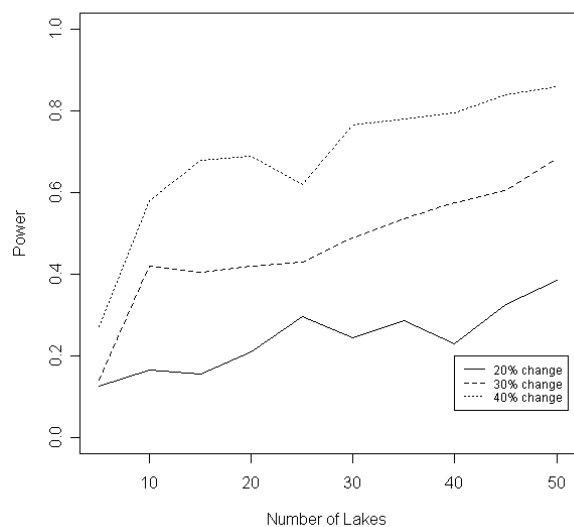


Figure B21. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0).

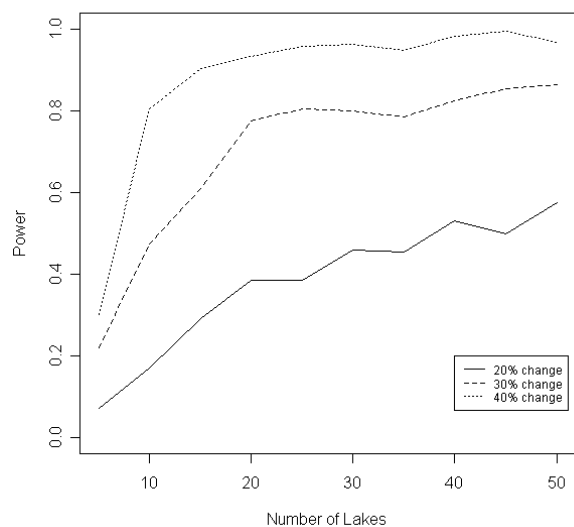


Figure B22. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,2-3).

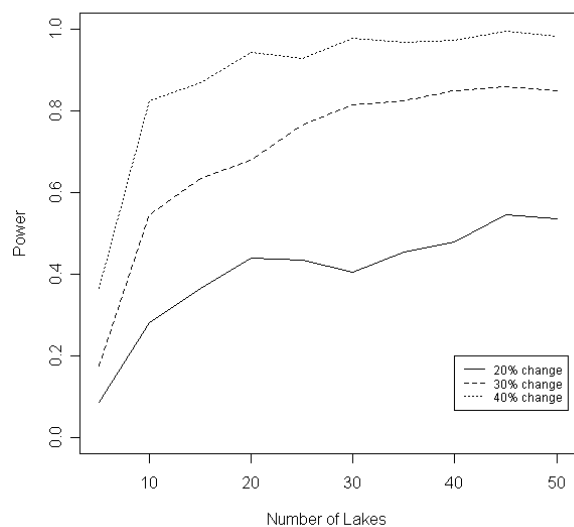


Figure B23. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,1-3).

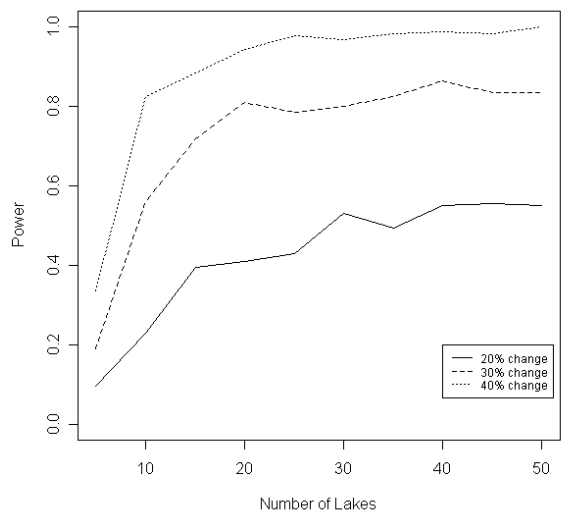


Figure B24. Power of trend detection for changes in fall ANC for annual surveys over 30 years; revisit = (1-0,2-5).

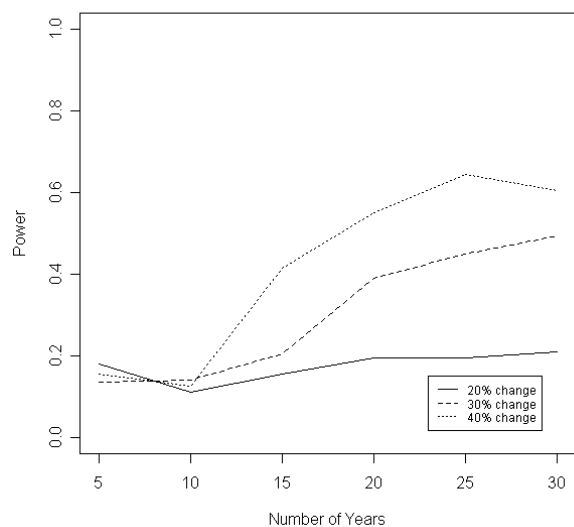


Figure B25. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0).

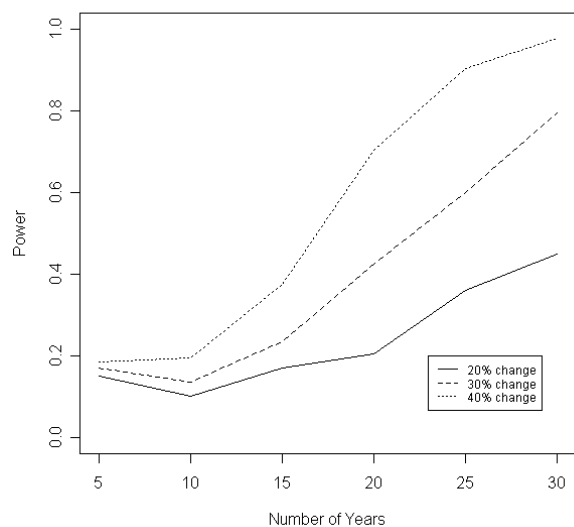


Figure B26. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,2-3).

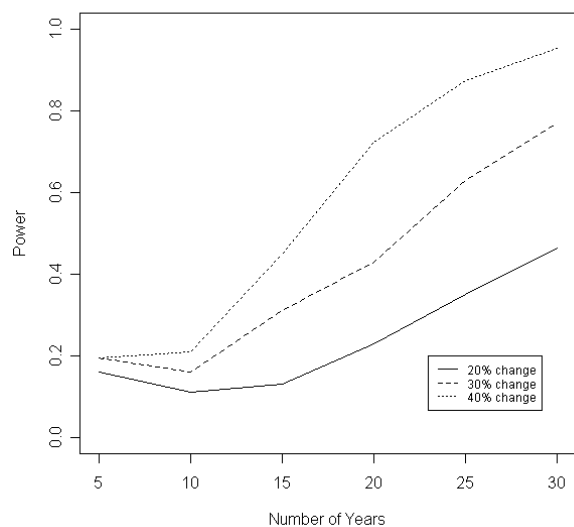


Figure B27. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,1-3).

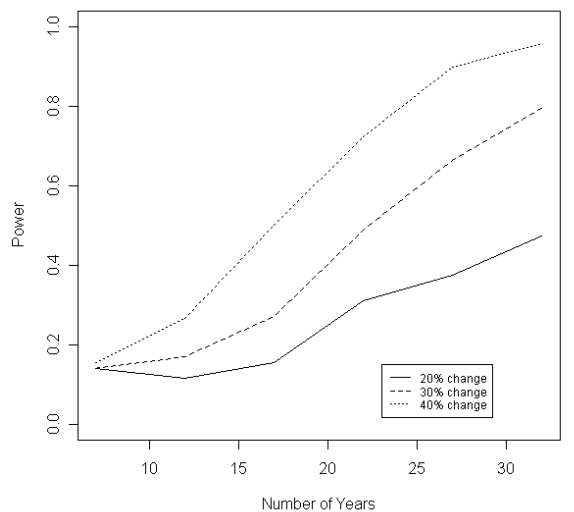


Figure B28. Power of trend detection for changes in fall ANC for annual surveys for 25 lakes; revisit = (1-0,2-5).

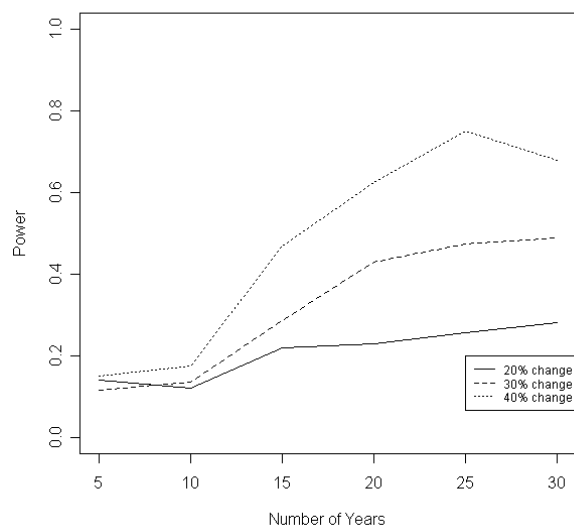


Figure B29. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0).

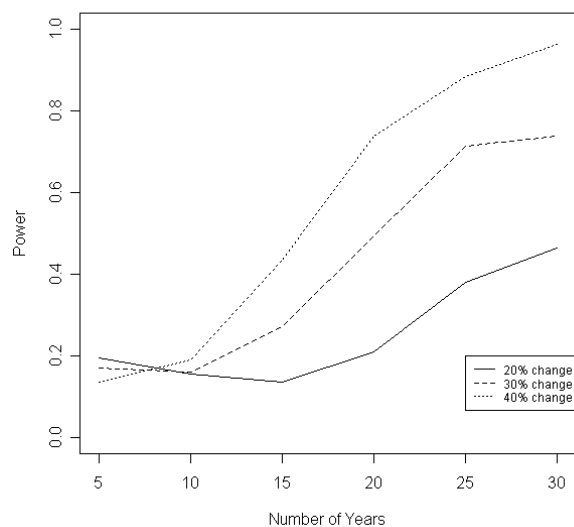


Figure B30. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,2-3).

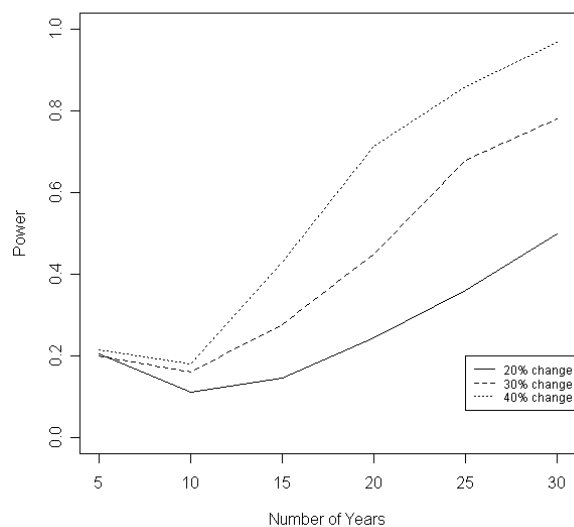


Figure B31. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,1-3).

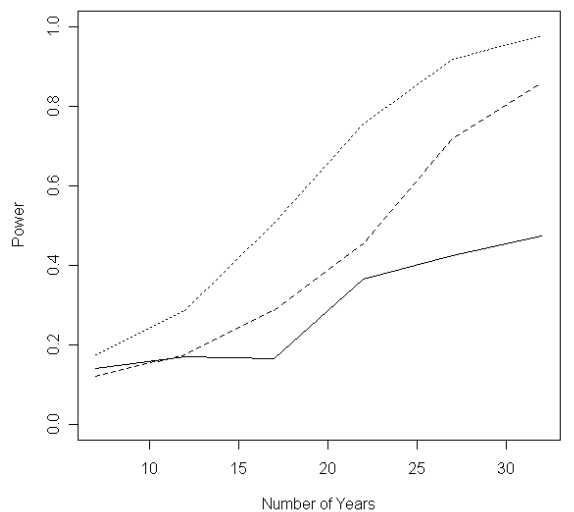


Figure B32. Power of trend detection for changes in fall ANC for annual surveys for 30 lakes; revisit = (1-0,2-5).

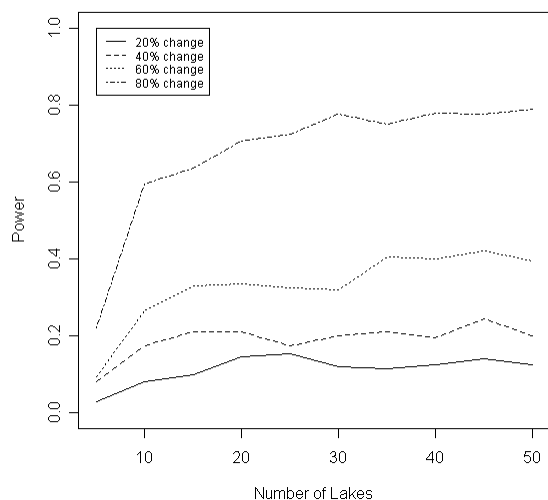


Figure B33. Power of trend detection for changes in fall NO₃ for annual surveys over 10 years; revisit = (1-0).

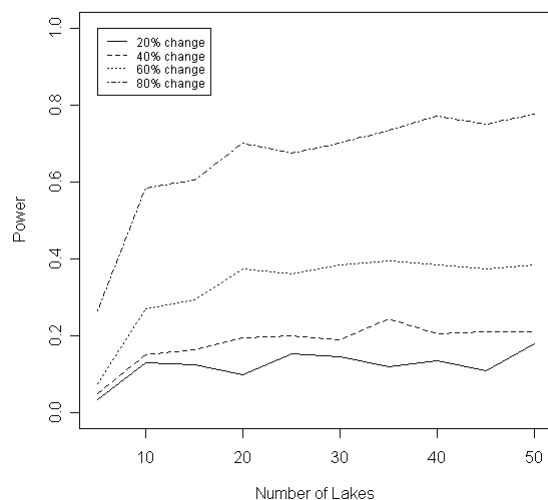


Figure B34. Power of trend detection for changes in fall NO₃ for annual surveys over 10 years; revisit = (1-0,2-3).

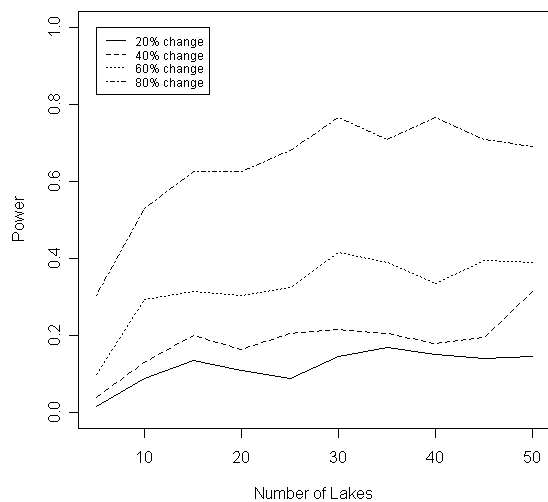


Figure B35. Power of trend detection for changes in fall NO₃ for annual surveys over 10 years; revisit = (1-0,1-3).

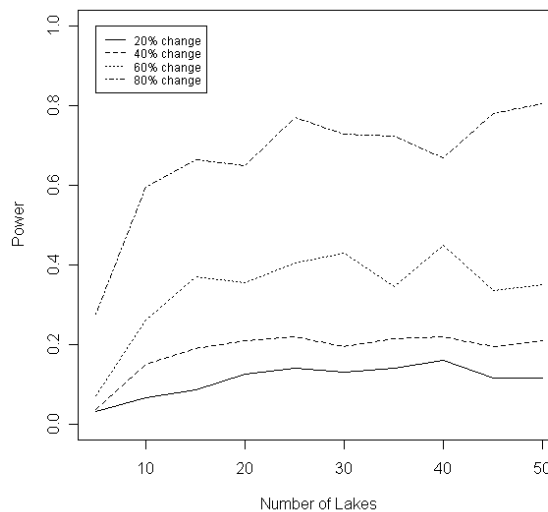


Figure B36. Power of trend detection for changes in fall NO₃ for annual surveys over 10 years; revisit = (1-0,2-5).

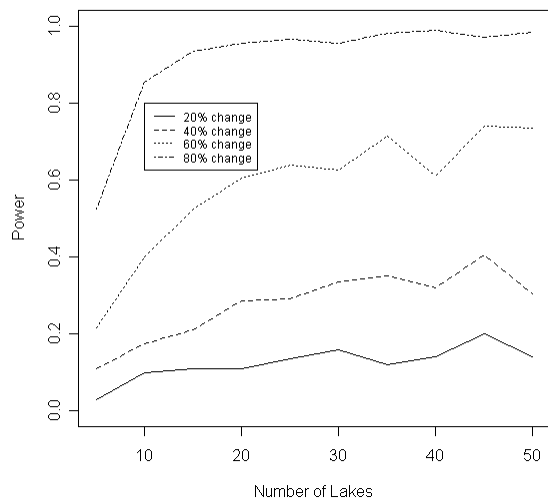


Figure B37. Power of trend detection for changes in fall NO₃ for annual surveys over 30 years; revisit = (1-0).

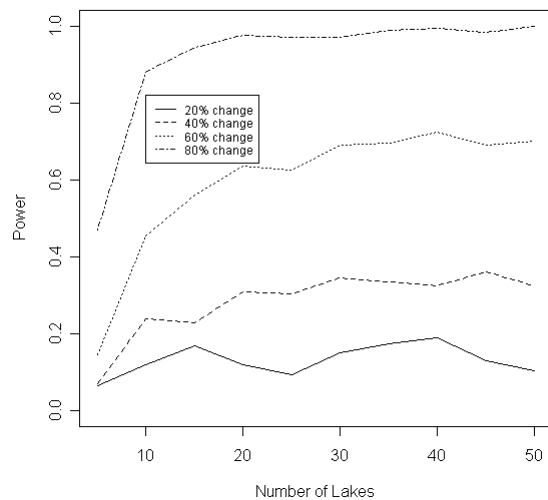


Figure B38. Power of trend detection for changes in fall NO₃ for annual surveys over 30 years; revisit = (1-0,2-3).

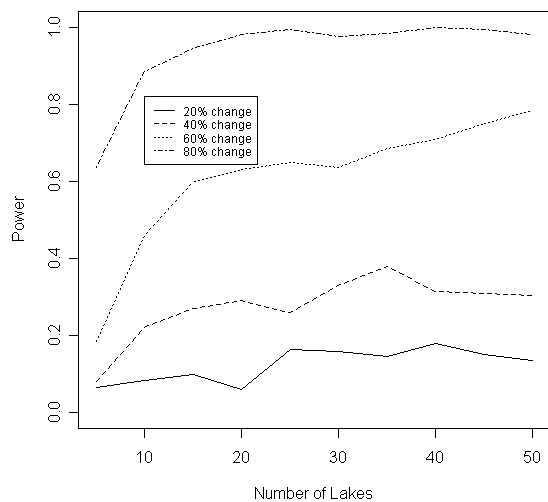


Figure B39. Power of trend detection for changes in fall NO₃ for annual surveys over 30 years; revisit = (1-0,1-3).

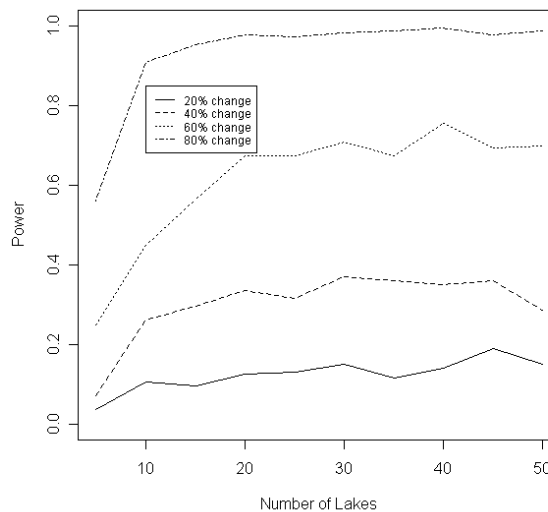


Figure B40. Power of trend detection for changes in fall NO₃ for annual surveys over 30 years; revisit = (1-0,2-5).

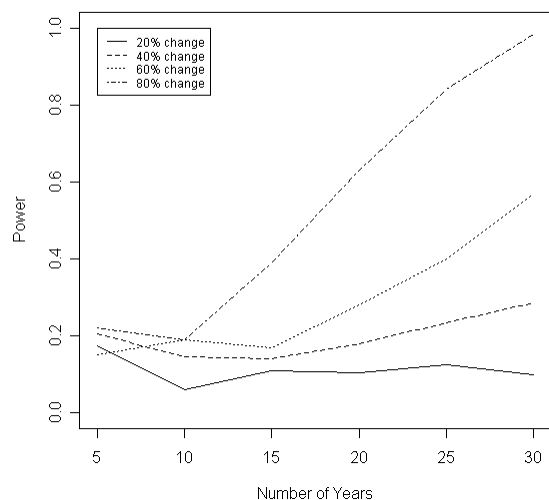


Figure B41. Power of trend detection for changes in fall NO₃ for annual surveys for 25 lakes; revisit = (1-0).

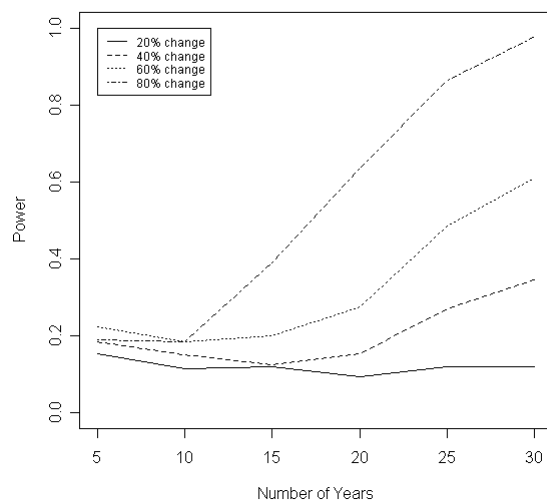


Figure B42. Power of trend detection for changes in fall NO₃ for annual surveys for 25 lakes; revisit = (1-0,2-3).

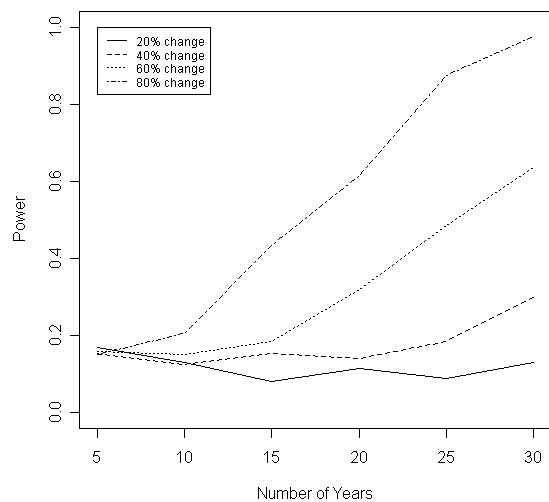


Figure B43. Power of trend detection for changes in fall NO₃ for annual surveys for 25 lakes; revisit = (1-0,1-3).

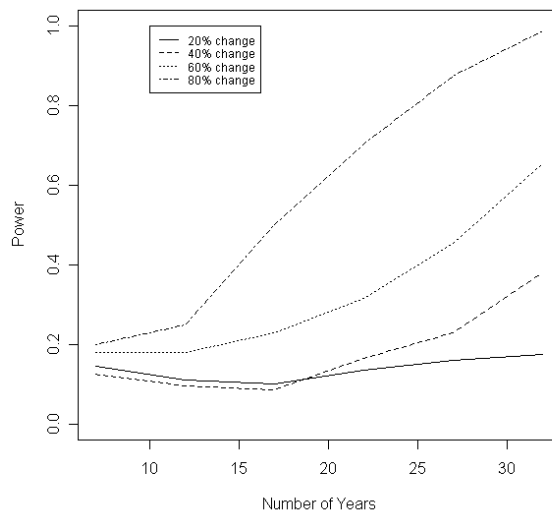


Figure B44. Power of trend detection for changes in fall NO₃ for annual surveys for 25 lakes; revisit = (1-0,2-5).

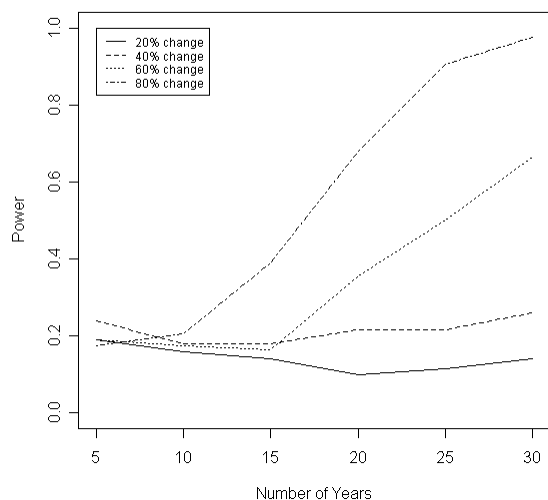


Figure B45. Power of trend detection for changes in fall NO₃ for annual surveys for 30 lakes; revisit = (1-0).

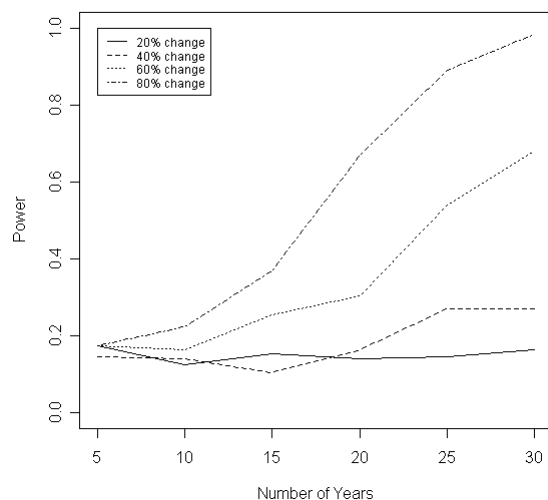


Figure B46. Power of trend detection for changes in fall NO₃ for annual surveys for 30 lakes; revisit = (1-0,2-3).

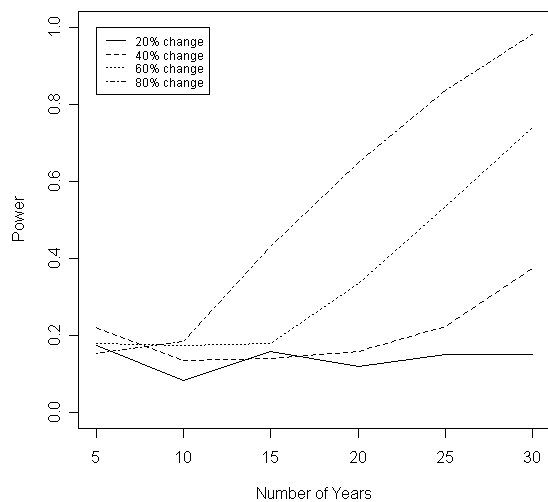


Figure B47. Power of trend detection for changes in fall NO₃ for annual surveys for 30 lakes; revisit = (1-0,1-3).

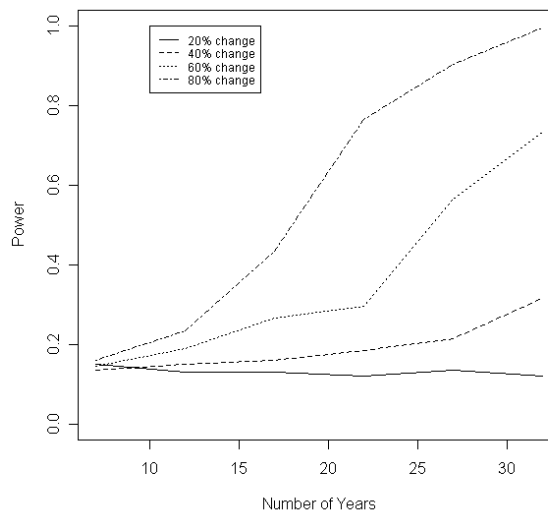


Figure B48. Power of trend detection for changes in fall NO₃ for annual surveys for 30 lakes; revisit = (1-0,2-5).

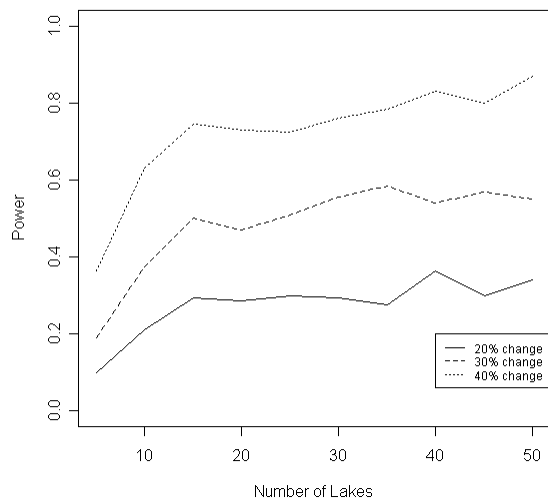


Figure B49. Power of trend detection for changes in fall SO_4 for annual surveys over 10 years; revisit = (1-0).

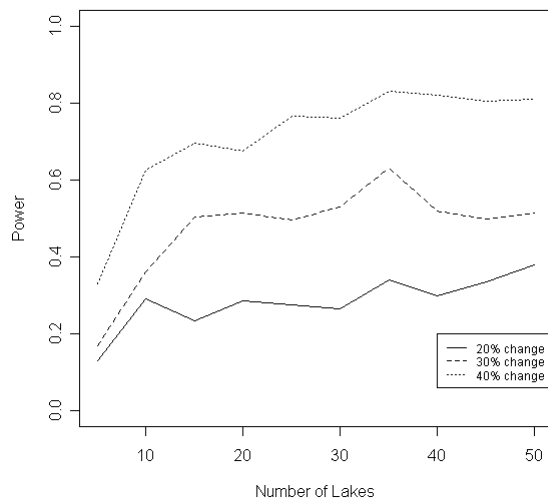


Figure B50. Power of trend detection for changes in fall SO_4 for annual surveys over 10 years; revisit = (1-0,2-3).

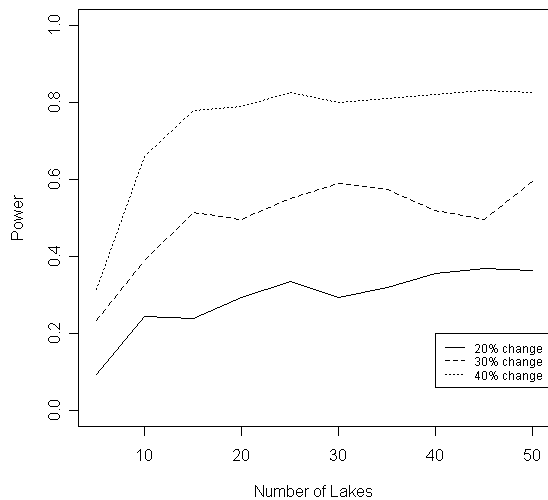


Figure B51. Power of trend detection for changes in fall SO_4 for annual surveys over 10 years; revisit = (1-0,1-3).

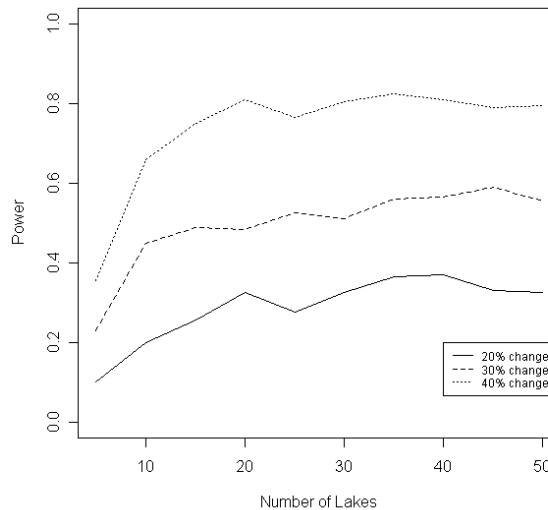


Figure B52. Power of trend detection for changes in fall SO_4 for annual surveys over 10 years; revisit = (1-0,2-5).

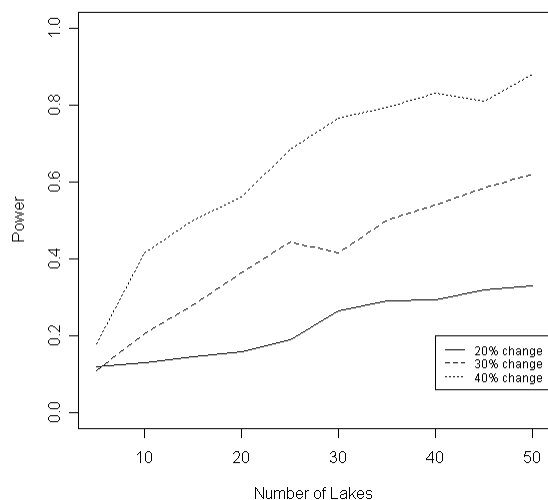


Figure B53. Power of trend detection for changes in fall SO_4 for annual surveys over 30 years; revisit = (1-0).

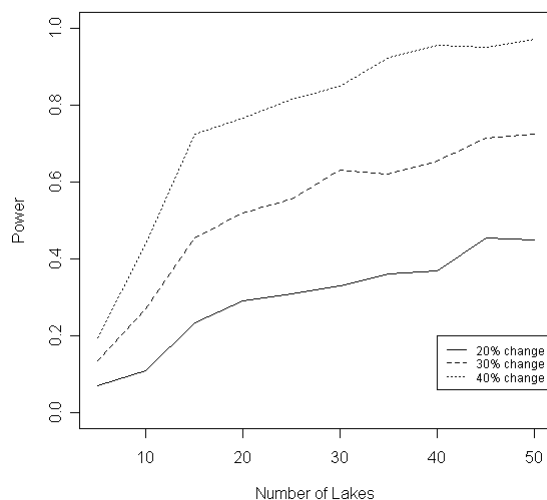


Figure B54. Power of trend detection for changes in fall SO_4 for annual surveys over 30 years; revisit = (1-0,2-3).

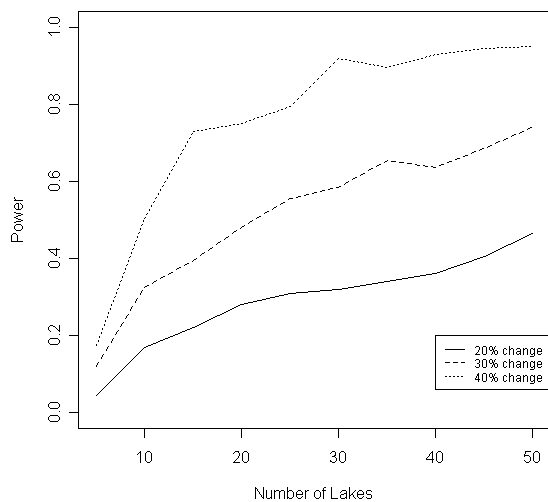


Figure B55. Power of trend detection for changes in fall SO_4 for annual surveys over 30 years; revisit = (1-0,1-3).

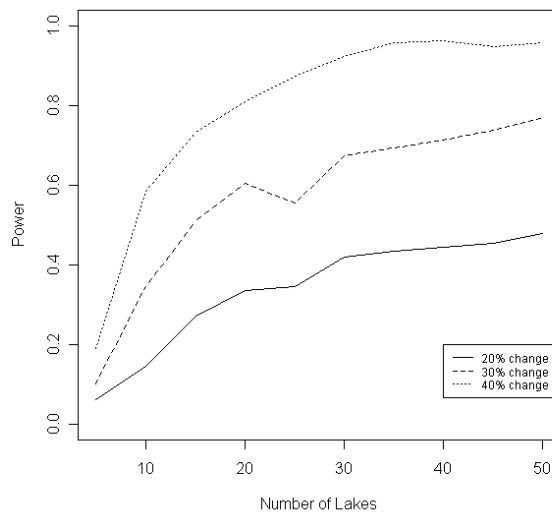


Figure B56. Power of trend detection for changes in fall SO_4 for annual surveys over 30 years; revisit = (1-0,2-5).

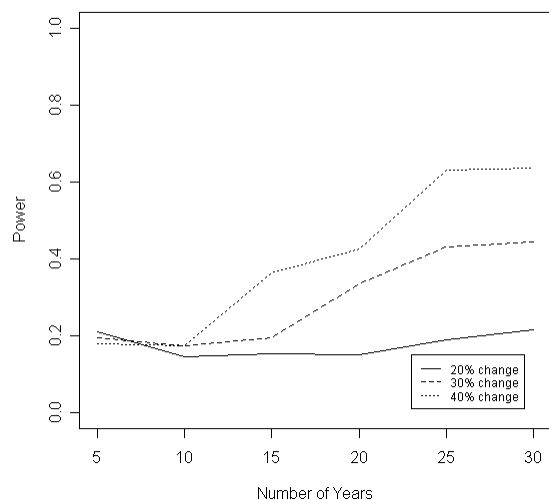


Figure B57. Power of trend detection for changes in fall SO₄ for annual surveys for 25 lakes; revisit = (1-0).

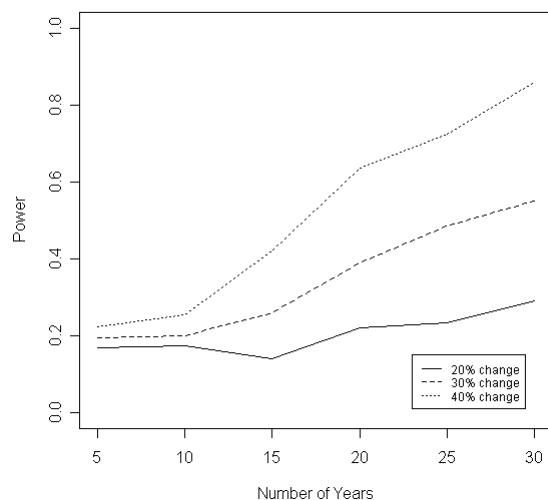


Figure B58. Power of trend detection for changes in fall SO₄ for annual surveys for 25 lakes; revisit = (1-0,2-3).

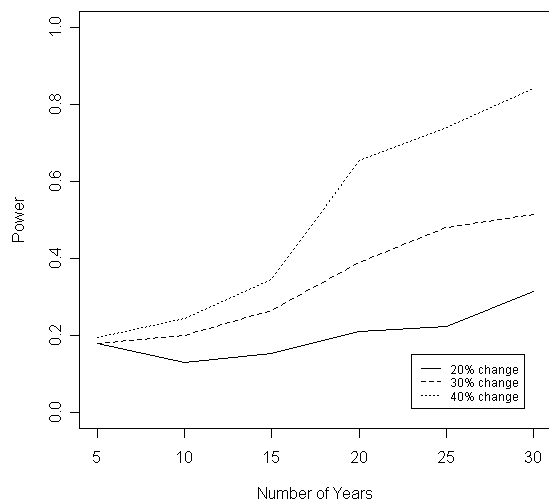


Figure B59. Power of trend detection for changes in fall SO₄ for annual surveys for 25 lakes; revisit = (1-0,1-3).

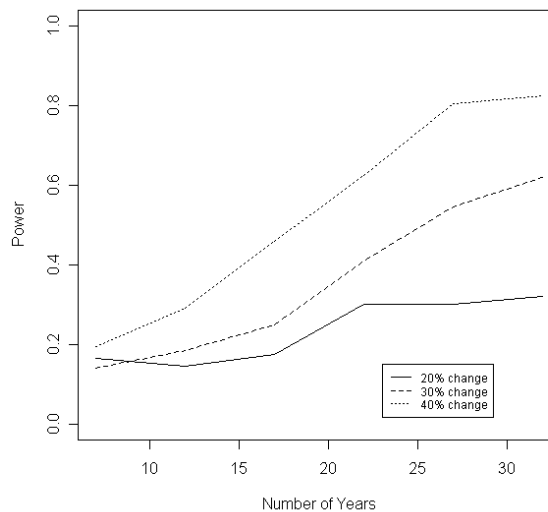


Figure B60. Power of trend detection for changes in fall SO₄ for annual surveys for 25 lakes; revisit = (1-0,2-5).

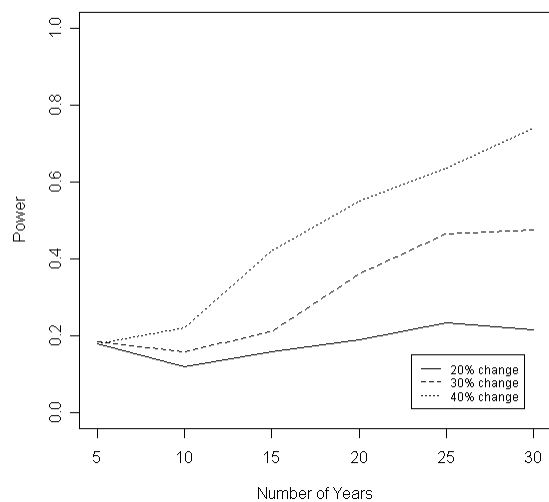


Figure B61. Power of trend detection for changes in fall SO₄ for annual surveys for 30 lakes; revisit = (1-0).

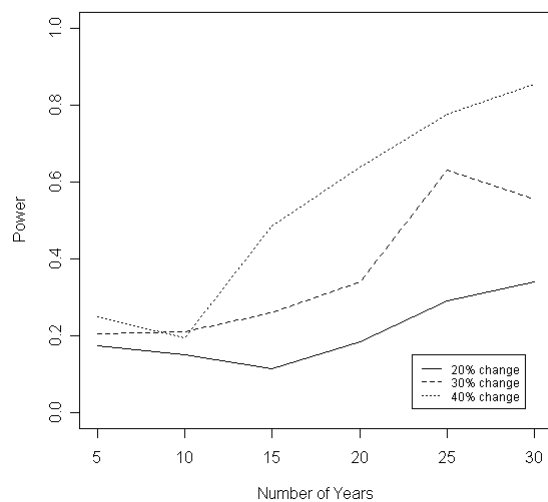


Figure B62. Power of trend detection for changes in fall SO₄ for annual surveys for 30 lakes; revisit = (1-0,2-3).

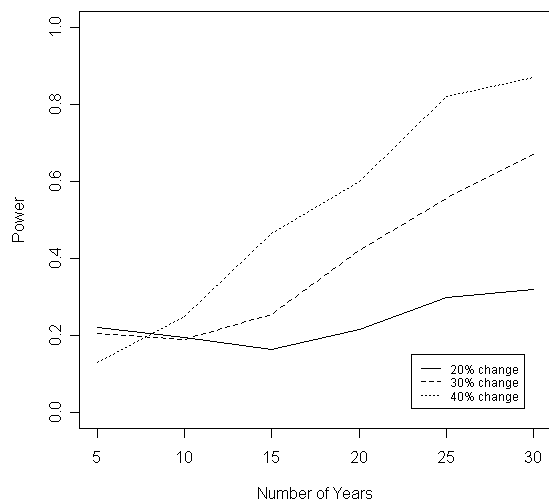


Figure B63. Power of trend detection for changes in fall SO₄ for annual surveys for 30 lakes; revisit = (1-0,1-3).

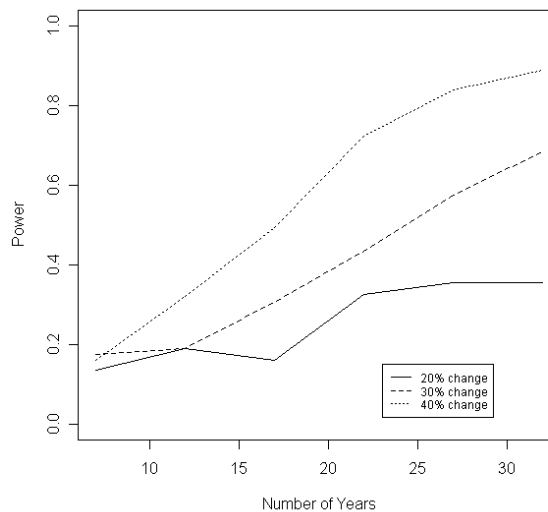


Figure B64. Power of trend detection for changes in fall SO₄ for annual surveys for 30 lakes; revisit = (1-0,2-5).

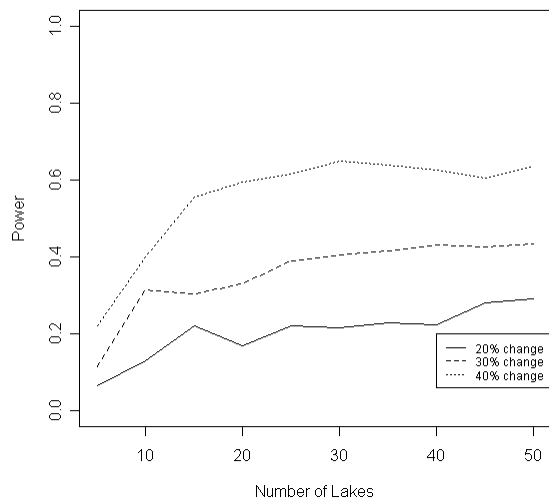


Figure B65. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0).

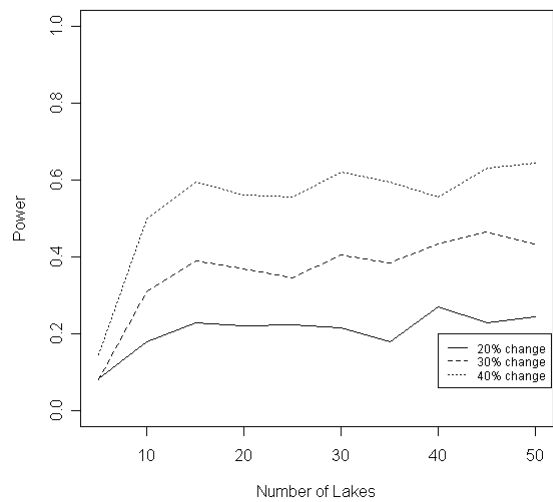


Figure B66. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,2-3).

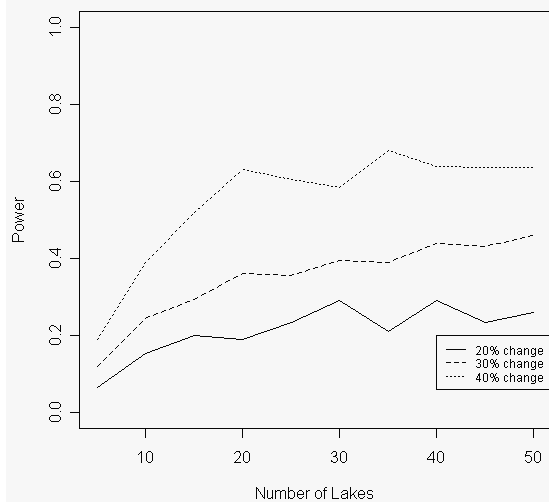


Figure B67. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,1-3).

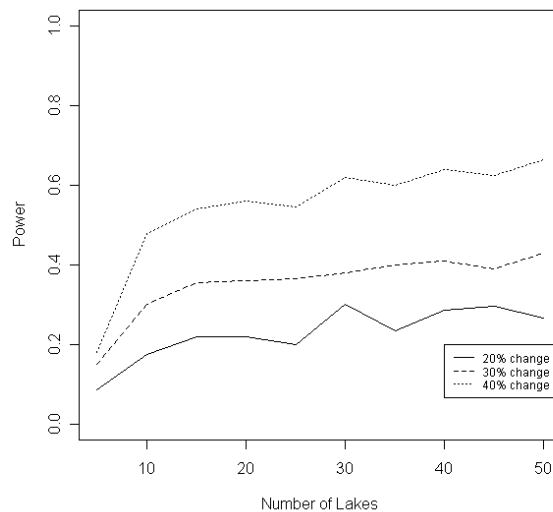


Figure B68. Power of trend detection for changes in fall PN for annual surveys over 10 years; revisit = (1-0,2-5).

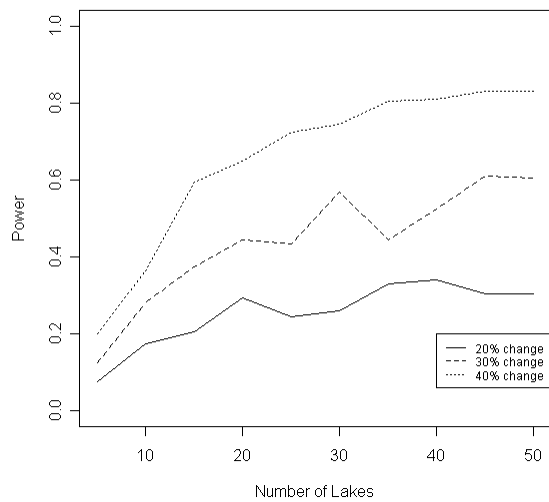


Figure B69. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0).

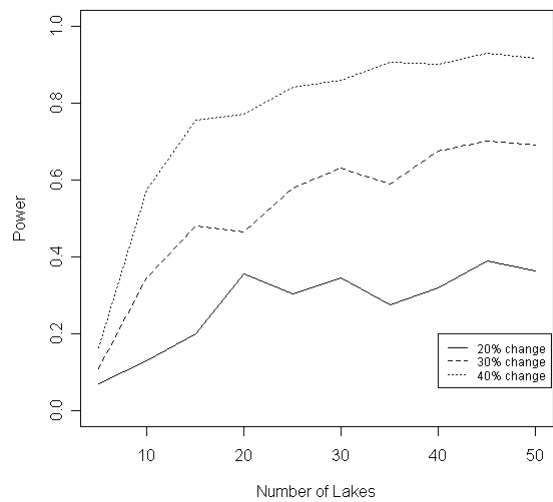


Figure B70. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,2-3).

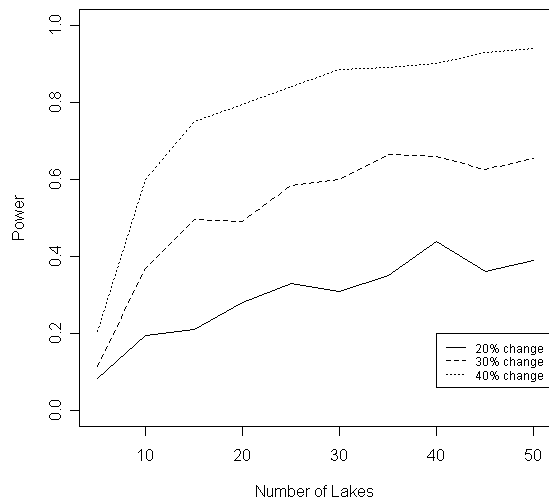


Figure B71. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,1-3).

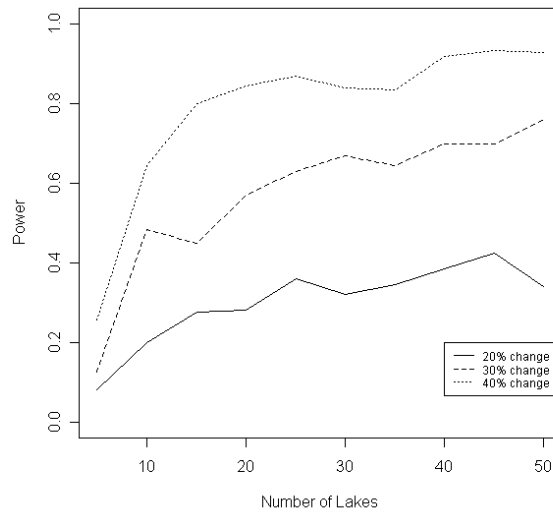


Figure B72. Power of trend detection for changes in fall PN for annual surveys over 30 years; revisit = (1-0,2-5).

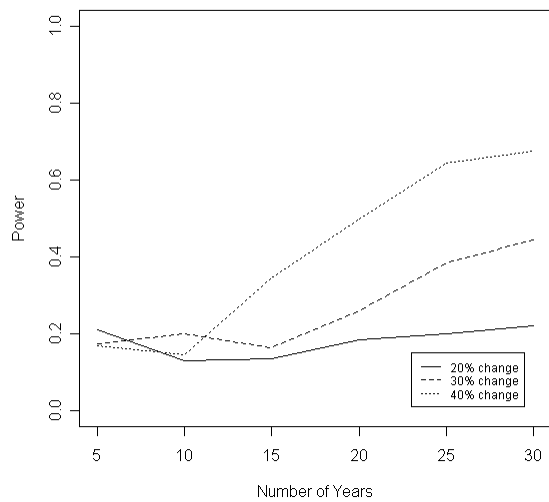


Figure B73. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0).

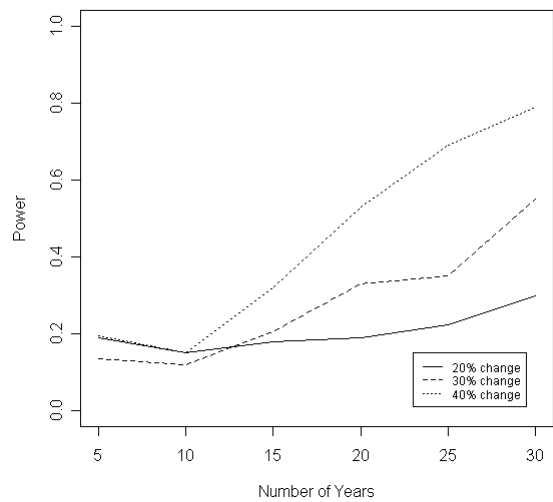


Figure B74. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,2-3).

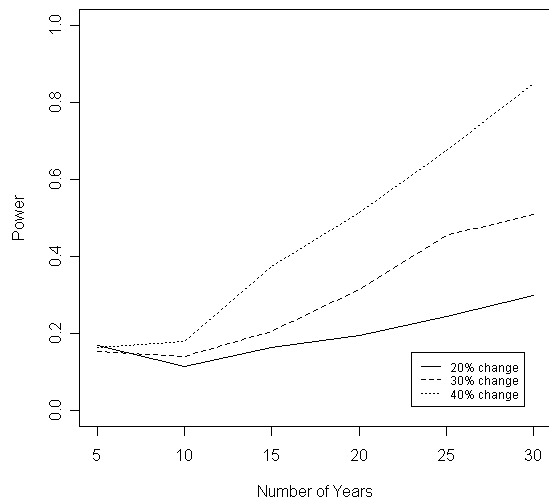


Figure B75. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,1-3).

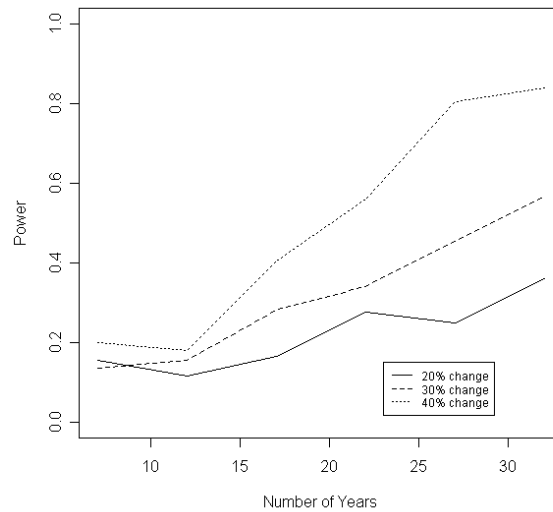


Figure B76. Power of trend detection for changes in fall PN for annual surveys for 25 lakes; revisit = (1-0,2-5).

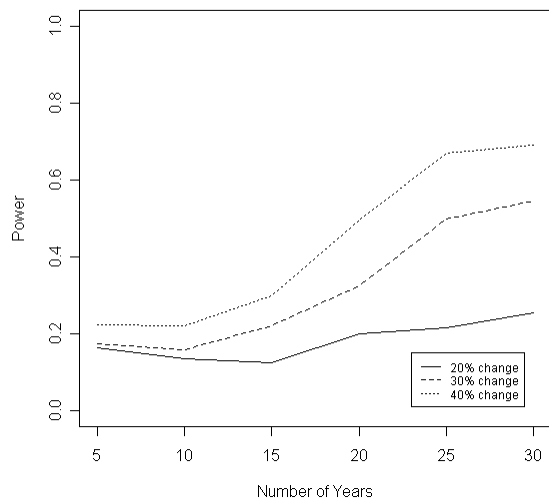


Figure B77. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0).

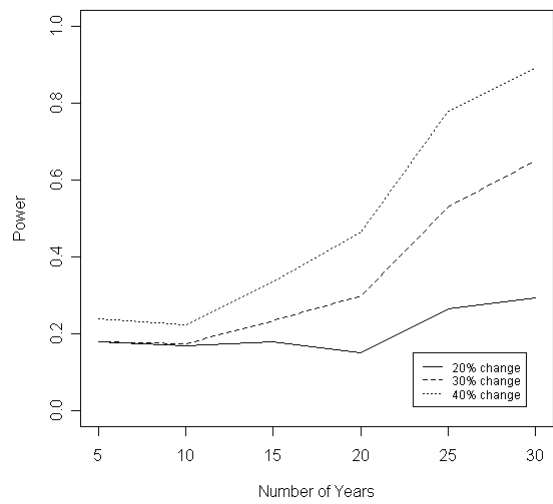


Figure B78. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-3).

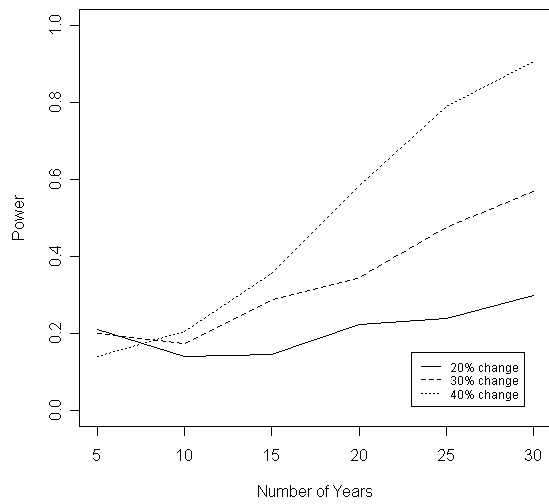


Figure B79. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,1-3).

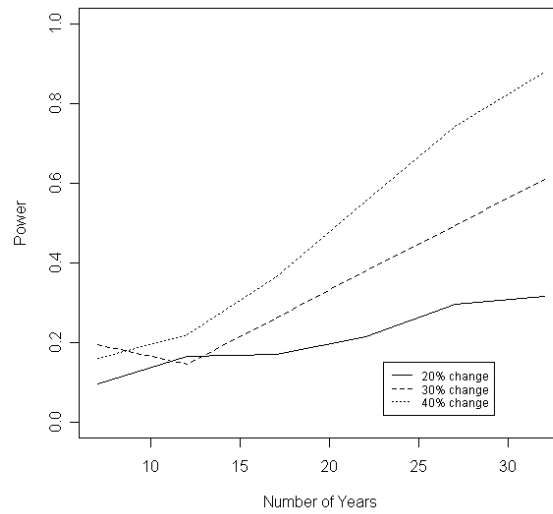


Figure B80. Power of trend detection for changes in fall PN for annual surveys for 30 lakes; revisit = (1-0,2-5).

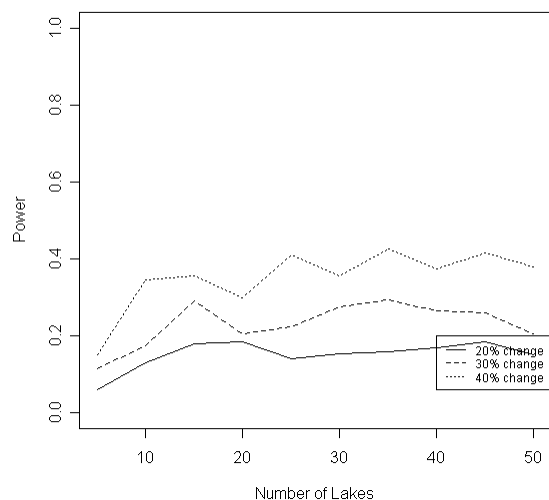


Figure B81. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0).

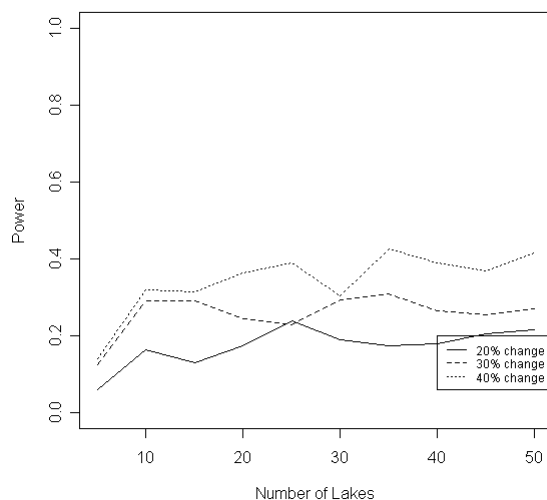


Figure B82. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,2-3).

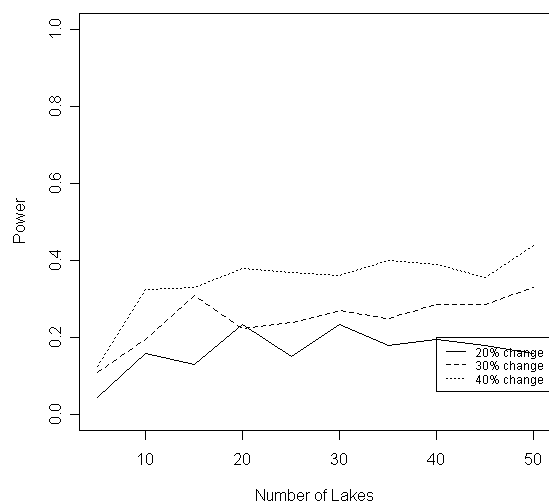


Figure B83. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,1-3).

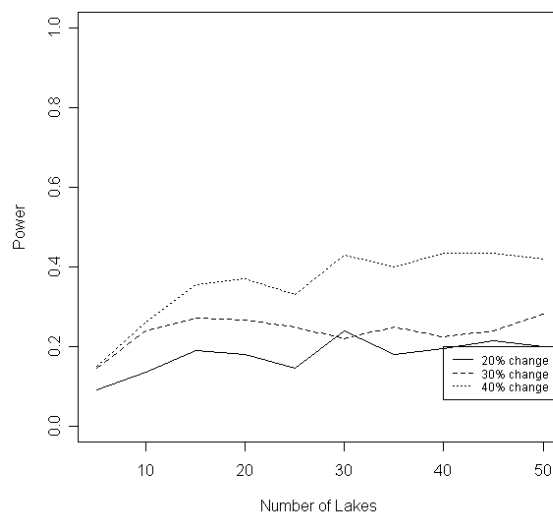


Figure B84. Power of trend detection for changes in fall PP for annual surveys over 10 years; revisit = (1-0,2-5).

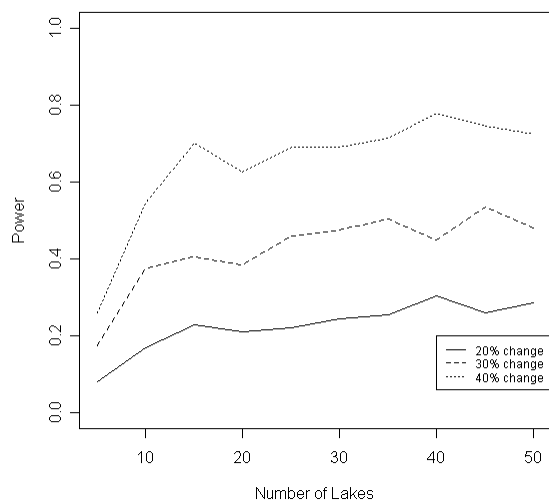


Figure B85. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0).

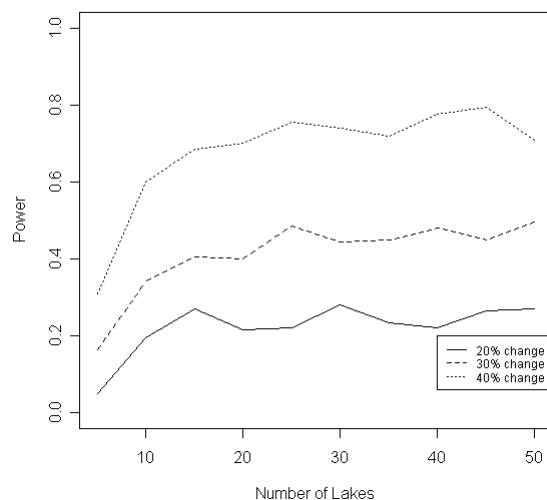


Figure B86. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0,2-3).

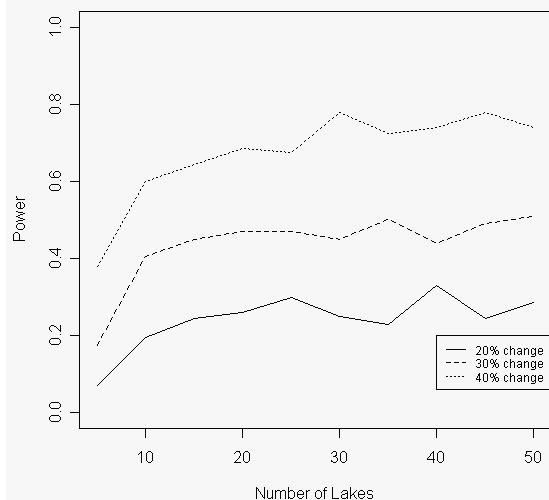


Figure B87. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0,1-3).

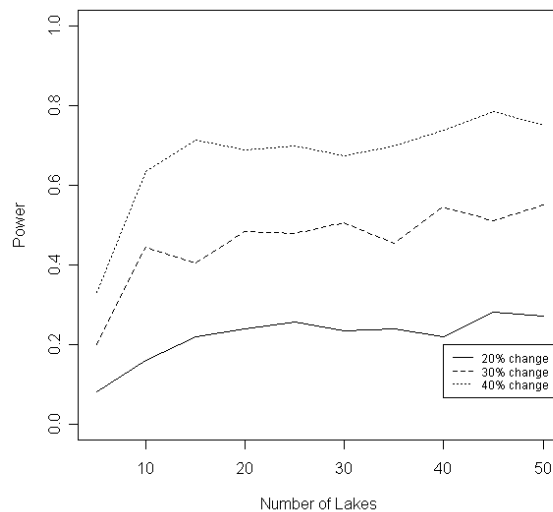


Figure B88. Power of trend detection for changes in fall PP for annual surveys over 30 years; revisit = (1-0,2-5).

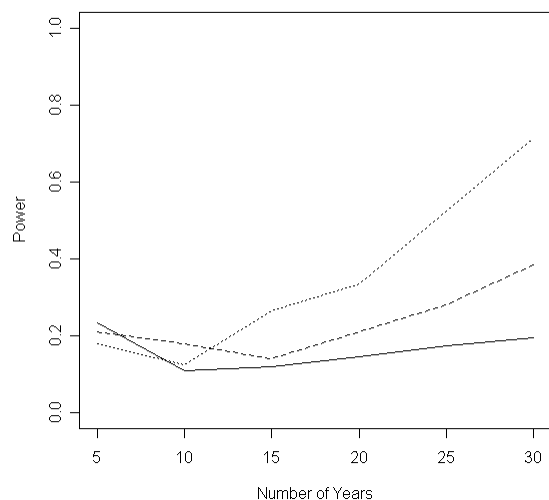


Figure B89. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0).

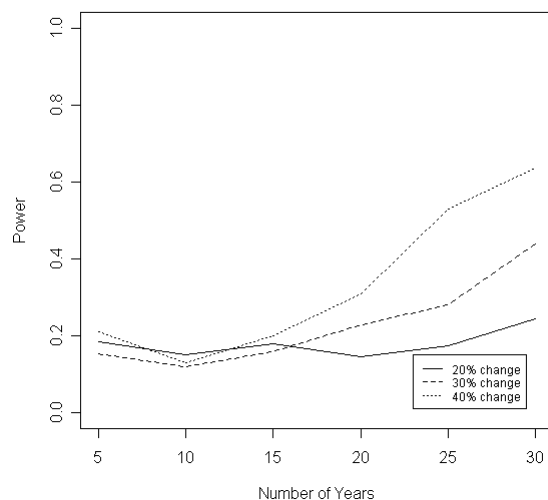


Figure B90. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,2-3).

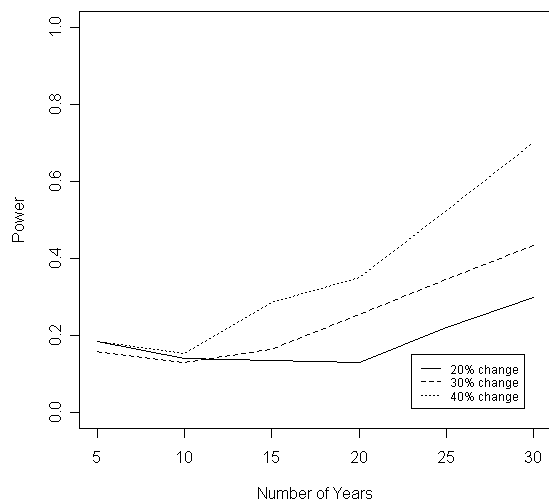


Figure B91. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,1-3).

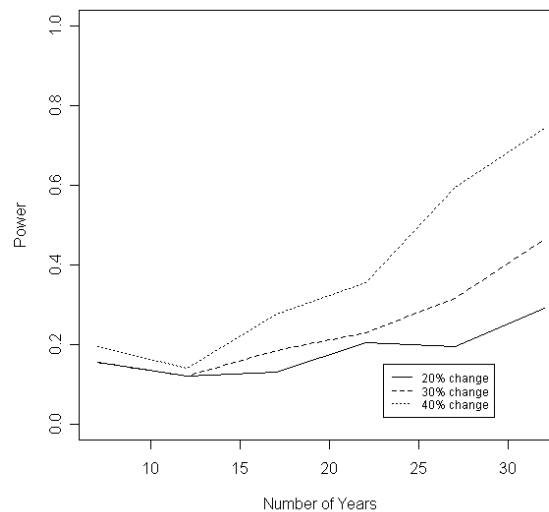


Figure B92. Power of trend detection for changes in fall PP for annual surveys for 25 lakes; revisit = (1-0,2-5).

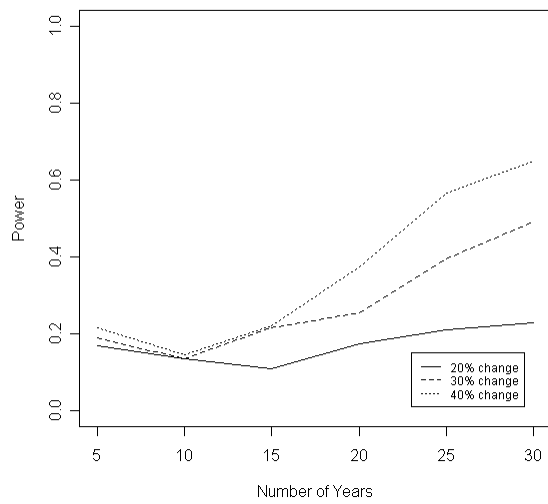


Figure B93. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0).

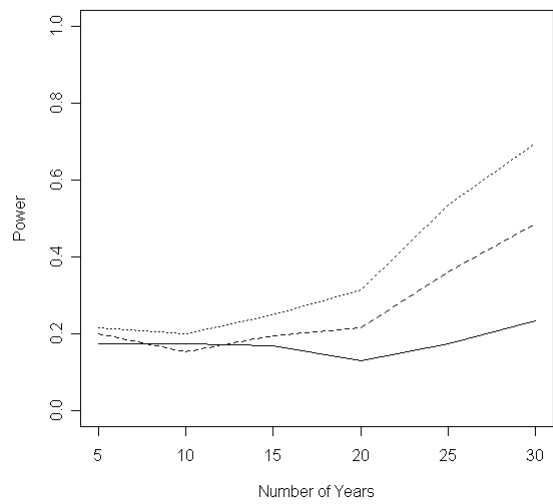


Figure B94. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-3).

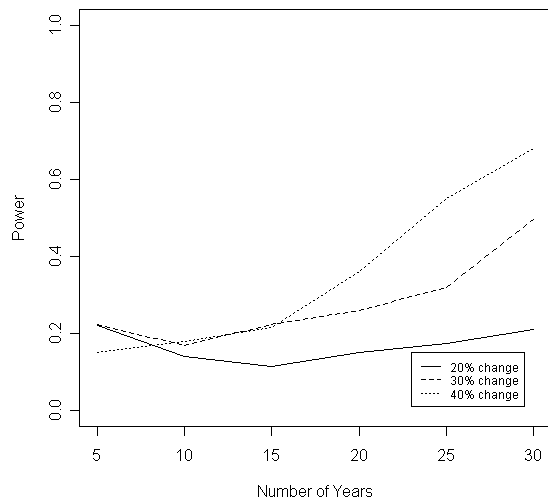


Figure B95. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,1-3).

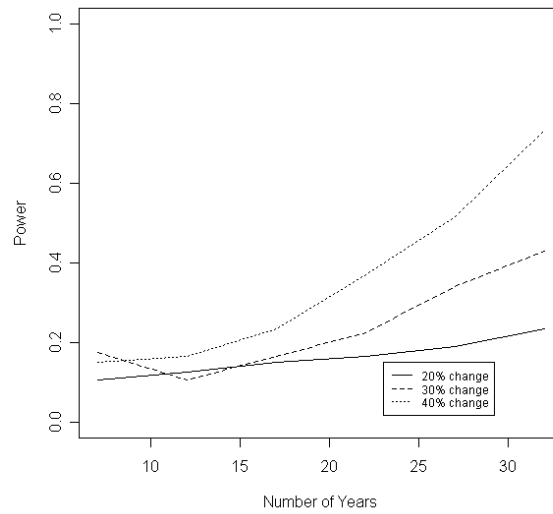


Figure B96. Power of trend detection for changes in fall PP for annual surveys for 30 lakes; revisit = (1-0,2-5).

Appendix C: Power Tables for Six Analytes and Four Revisit Designs

Note: All simulated population changes are declines.

Tables

	Pages
Table C1. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years.	73
Table C2. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years.	73
Table C3. Power of trend detection for changes in fall specific conductance for annual surveys of 25 lakes.	74
Table C4. Power of trend detection for changes in fall specific conductance for annual surveys of 30 lakes.	74
Table C5. Power of trend detection for changes in fall ANC for annual surveys over 10 years.	75
Table C6. Power of trend detection for changes in fall ANC for annual surveys over 30 years.	76
Table C7. Power of trend detection for changes in fall ANC for annual surveys of 25 lakes.	76
Table C8. Power of trend detection for changes in fall ANC for annual surveys of 30 lakes.	77
Table C9. Power of trend detection for changes in fall NO ₃ for annual surveys over 10 years.	77
Table C10. Power of trend detection for changes in fall NO ₃ for annual surveys over 30 years.	78
Table C11. Power of trend detection for changes in fall NO ₃ for annual surveys of 25 lakes.	78
Table C12. Power of trend detection for changes in fall NO ₃ for annual surveys of 30 lakes.	79
Table C13. Power of trend detection for changes in fall SO ₄ for annual surveys over 10 years.	79

Tables (continued)

	Pages
Table C14. Power of trend detection for changes in fall SO ₄ for annual surveys over 30 years.	80
Table C15. Power of trend detection for changes in fall SO ₄ for annual surveys of 25 lakes.	80
Table C16. Power of trend detection for changes in fall SO ₄ for annual surveys of 30 lakes.	81
Table C17. Power of trend detection for changes in fall PN for annual surveys over 10 years.	81
Table C18. Power of trend detection for changes in fall PN for annual surveys over 30 years.	82
Table C19. Power of trend detection for changes in fall PN for annual surveys of 25 lakes.	82
Table C20. Power of trend detection for changes in fall PN for annual surveys of 30 lakes.	83
Table C21. Power of trend detection for changes in fall PP for annual surveys over 10 years.	83
Table C22. Power of trend detection for changes in fall PP for annual surveys over 30 years.	84
Table C23. Power of trend detection for changes in fall PP for annual surveys of 25 lakes.	84
Table C24. Power of trend detection for changes in fall PP for annual surveys of 30 lakes.	85

Table C1. Power of trend detection for changes in fall specific conductance for annual surveys over 10 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.185	0.480	0.775	0.205	0.365	0.625	0.200	0.440	0.775	0.230	0.475	0.760
10	0.510	0.780	0.975	0.440	0.865	0.990	0.510	0.900	0.995	0.435	0.790	0.980
15	0.515	0.935	0.995	0.565	0.915	1.000	0.585	0.885	0.995	0.520	0.885	1.000
20	0.680	0.960	1.000	0.635	0.930	0.995	0.655	0.935	1.000	0.630	0.865	1.000
25	0.695	0.940	1.000	0.605	0.935	1.000	0.650	0.955	1.000	0.565	0.885	0.990
30	0.675	0.975	0.995	0.725	0.945	1.000	0.725	0.950	1.000	0.645	0.925	1.000
35	0.750	0.975	1.000	0.735	0.960	1.000	0.750	0.945	1.000	0.650	0.925	0.995
40	0.675	0.980	1.000	0.700	0.980	1.000	0.705	0.990	1.000	0.690	0.960	1.000
45	0.730	0.970	1.000	0.785	0.970	0.995	0.765	0.970	1.000	0.690	0.960	1.000
50	0.735	0.985	0.995	0.730	0.960	0.995	0.795	0.980	1.000	0.685	0.940	1.000

Table C2. Power of trend detection for changes in fall specific conductance for annual surveys over 30 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.140	0.270	0.435	0.145	0.260	0.430	0.105	0.255	0.455	0.130	0.270	0.485
10	0.225	0.490	0.745	0.300	0.670	0.930	0.390	0.665	0.940	0.325	0.685	0.940
15	0.350	0.705	0.890	0.495	0.870	0.995	0.430	0.895	0.985	0.510	0.845	0.975
20	0.480	0.825	0.960	0.515	0.900	0.995	0.600	0.945	0.995	0.570	0.930	0.995
25	0.490	0.830	0.990	0.685	0.940	1.000	0.645	0.970	1.000	0.590	0.935	1.000
30	0.560	0.900	0.990	0.745	0.985	1.000	0.765	0.985	1.000	0.765	0.970	1.000
35	0.600	0.905	1.000	0.745	0.980	1.000	0.800	0.990	1.000	0.740	0.990	1.000
40	0.660	0.975	1.000	0.830	0.995	1.000	0.755	0.990	1.000	0.820	0.990	1.000
45	0.660	0.970	1.000	0.825	0.990	1.000	0.835	0.990	1.000	0.840	1.000	1.000
50	0.675	0.980	1.000	0.825	0.995	1.000	0.845	0.995	1.000	0.835	0.990	1.000

Table C3. Power of trend detection for changes in fall specific conductance for annual surveys of 25 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.220	0.160	0.215	0.150	0.155	0.165	0.225	0.205	0.200	0.190	0.175	0.255
10	0.190	0.280	0.455	0.210	0.295	0.405	0.180	0.300	0.445	0.215	0.380	0.560
15	0.200	0.520	0.750	0.270	0.540	0.820	0.310	0.560	0.820	0.335	0.610	0.870
20	0.355	0.635	0.915	0.435	0.790	0.975	0.450	0.800	0.950	0.510	0.790	0.980
25	0.400	0.805	0.970	0.625	0.875	0.990	0.595	0.875	0.995	0.655	0.920	1.000
30	0.530	0.760	0.975	0.670	0.950	1.000	0.615	0.960	1.000	0.665	0.945	0.995

Table C4. Power of trend detection for changes in fall specific conductance for annual surveys of 30 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.185	0.195	0.225	0.175	0.195	0.180	0.210	0.195	0.200	0.160	0.175	0.290
10	0.140	0.305	0.395	0.245	0.335	0.445	0.140	0.310	0.475	0.250	0.345	0.605
15	0.270	0.510	0.825	0.305	0.525	0.845	0.270	0.540	0.830	0.305	0.615	0.910
20	0.410	0.790	0.955	0.430	0.835	0.980	0.560	0.870	0.990	0.580	0.865	0.990
25	0.475	0.815	0.975	0.625	0.955	0.995	0.680	0.955	0.995	0.620	0.965	0.995
30	0.620	0.875	0.995	0.725	0.960	1.000	0.685	0.970	1.000	0.705	0.975	1.000

Table C5. Power of trend detection for changes in fall ANC for annual surveys over 10 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.095	0.260	0.470	0.095	0.260	0.525	0.145	0.300	0.500	0.130	0.280	0.505
10	0.205	0.395	0.650	0.260	0.505	0.710	0.260	0.480	0.705	0.220	0.505	0.770
15	0.260	0.435	0.730	0.300	0.430	0.755	0.260	0.450	0.775	0.265	0.520	0.760
20	0.265	0.445	0.670	0.295	0.410	0.760	0.270	0.465	0.755	0.330	0.520	0.805
25	0.250	0.435	0.605	0.200	0.480	0.765	0.315	0.505	0.780	0.270	0.515	0.765
30	0.215	0.420	0.685	0.270	0.480	0.700	0.295	0.495	0.785	0.315	0.490	0.840
35	0.190	0.485	0.675	0.325	0.535	0.735	0.285	0.520	0.745	0.345	0.555	0.805
40	0.270	0.450	0.660	0.325	0.475	0.735	0.310	0.485	0.745	0.375	0.555	0.785
45	0.210	0.415	0.670	0.260	0.505	0.775	0.325	0.520	0.735	0.325	0.575	0.790
50	0.255	0.440	0.730	0.225	0.465	0.765	0.265	0.500	0.745	0.300	0.570	0.820

Table C6. Power of trend detection for changes in fall ANC for annual surveys over 30 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.125	0.140	0.270	0.070	0.220	0.300	0.085	0.175	0.365	0.095	0.190	0.335
10	0.165	0.420	0.580	0.170	0.475	0.805	0.280	0.545	0.825	0.230	0.560	0.825
15	0.155	0.405	0.680	0.290	0.610	0.905	0.365	0.635	0.870	0.395	0.720	0.885
20	0.210	0.420	0.690	0.385	0.775	0.935	0.440	0.680	0.945	0.410	0.810	0.945
25	0.295	0.430	0.620	0.385	0.805	0.960	0.435	0.765	0.930	0.430	0.785	0.980
30	0.245	0.490	0.765	0.460	0.800	0.965	0.405	0.815	0.980	0.530	0.800	0.970
35	0.285	0.535	0.780	0.455	0.785	0.950	0.455	0.825	0.970	0.495	0.825	0.985
40	0.230	0.575	0.795	0.530	0.825	0.985	0.480	0.850	0.975	0.550	0.865	0.990
45	0.325	0.605	0.840	0.500	0.855	0.995	0.545	0.860	0.995	0.555	0.835	0.985
50	0.385	0.685	0.860	0.575	0.865	0.970	0.535	0.850	0.985	0.550	0.835	1.000

Table C7. Power of trend detection for changes in fall ANC for annual surveys of 25 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.180	0.135	0.155	0.150	0.170	0.185	0.160	0.195	0.195	0.140	0.140	0.155
10	0.110	0.140	0.125	0.100	0.135	0.195	0.110	0.160	0.210	0.115	0.170	0.265
15	0.155	0.205	0.415	0.170	0.235	0.375	0.130	0.310	0.450	0.155	0.270	0.500
20	0.195	0.390	0.550	0.205	0.425	0.705	0.230	0.430	0.725	0.310	0.490	0.725
25	0.195	0.450	0.645	0.360	0.600	0.905	0.350	0.630	0.875	0.375	0.665	0.900
30	0.210	0.495	0.605	0.450	0.795	0.980	0.465	0.770	0.955	0.475	0.795	0.960

Table C8. Power of trend detection for changes in fall ANC for annual surveys of 30 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.140	0.115	0.150	0.195	0.170	0.135	0.205	0.200	0.215	0.140	0.120	0.175
10	0.120	0.135	0.175	0.155	0.160	0.190	0.110	0.160	0.180	0.170	0.175	0.285
15	0.220	0.285	0.470	0.135	0.270	0.435	0.145	0.275	0.430	0.165	0.285	0.505
20	0.230	0.430	0.625	0.210	0.495	0.740	0.245	0.450	0.715	0.365	0.455	0.755
25	0.255	0.475	0.750	0.380	0.715	0.885	0.360	0.680	0.860	0.425	0.720	0.920
30	0.280	0.490	0.680	0.465	0.740	0.965	0.500	0.780	0.970	0.475	0.860	0.980

Table C9. Power of trend detection for changes in fall NO₃ for annual surveys over 10 years.

Lakes	[1-0]				[(1-0),(2-3)]				[(1-0),(1-3)]				[(1-0),(2-5)]			
	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.030	0.080	0.095	0.220	0.035	0.050	0.075	0.265	0.015	0.040	0.100	0.305	0.030	0.035	0.070	0.275
10	0.080	0.175	0.265	0.595	0.130	0.150	0.270	0.585	0.090	0.130	0.295	0.530	0.065	0.150	0.260	0.595
15	0.100	0.210	0.330	0.635	0.125	0.165	0.295	0.605	0.135	0.200	0.315	0.625	0.085	0.190	0.370	0.665
20	0.145	0.210	0.335	0.705	0.100	0.195	0.375	0.700	0.110	0.165	0.305	0.625	0.125	0.210	0.355	0.650
25	0.155	0.175	0.325	0.725	0.155	0.200	0.360	0.675	0.090	0.205	0.325	0.680	0.140	0.220	0.405	0.770
30	0.120	0.200	0.320	0.775	0.145	0.190	0.385	0.700	0.145	0.215	0.415	0.765	0.130	0.195	0.430	0.730
35	0.115	0.210	0.405	0.750	0.120	0.245	0.395	0.735	0.170	0.205	0.390	0.710	0.140	0.215	0.345	0.725
40	0.125	0.195	0.400	0.780	0.135	0.205	0.385	0.770	0.150	0.180	0.335	0.765	0.160	0.220	0.450	0.670
45	0.140	0.245	0.420	0.775	0.110	0.210	0.375	0.750	0.140	0.195	0.395	0.710	0.115	0.195	0.335	0.780
50	0.125	0.200	0.395	0.790	0.180	0.210	0.385	0.775	0.145	0.315	0.390	0.690	0.115	0.210	0.350	0.805

Table C10. Power of trend detection for changes in fall NO₃ for annual surveys over 30 years.

Lakes	[1-0]				[(1-0),(2-3)]				[(1-0),(1-3)]				[(1-0),(2-5)]			
	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.030	0.110	0.215	0.525	0.065	0.070	0.145	0.470	0.065	0.080	0.185	0.635	0.035	0.070	0.250	0.560
10	0.100	0.175	0.400	0.855	0.120	0.240	0.455	0.880	0.085	0.220	0.460	0.885	0.105	0.260	0.450	0.910
15	0.110	0.210	0.525	0.935	0.170	0.230	0.560	0.945	0.100	0.270	0.600	0.945	0.095	0.295	0.565	0.955
20	0.110	0.285	0.605	0.955	0.120	0.310	0.635	0.975	0.060	0.290	0.630	0.980	0.125	0.335	0.675	0.980
25	0.135	0.290	0.640	0.965	0.095	0.305	0.625	0.970	0.165	0.260	0.650	0.995	0.130	0.315	0.675	0.975
30	0.160	0.335	0.625	0.955	0.150	0.345	0.690	0.970	0.160	0.330	0.635	0.975	0.150	0.370	0.710	0.985
35	0.120	0.350	0.715	0.980	0.175	0.335	0.695	0.990	0.145	0.380	0.685	0.985	0.115	0.360	0.675	0.990
40	0.140	0.320	0.610	0.990	0.190	0.325	0.725	0.995	0.180	0.315	0.710	1.000	0.140	0.350	0.755	0.995
45	0.200	0.405	0.740	0.970	0.130	0.360	0.690	0.985	0.150	0.310	0.750	0.995	0.190	0.360	0.695	0.980
50	0.140	0.305	0.735	0.985	0.105	0.325	0.700	1.000	0.135	0.305	0.785	0.980	0.150	0.285	0.700	0.990

Table C11. Power of trend detection for changes in fall NO₃ for annual surveys of 25 lakes.

Years	[1-0]				[(1-0),(2-3)]				[(1-0),(1-3)]				[(1-0),(2-5)]			
	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.175	0.205	0.15	0.220	0.155	0.185	0.225	0.190	0.170	0.155	0.160	0.150	0.145	0.125	0.180	0.200
10	0.060	0.145	0.19	0.190	0.115	0.150	0.185	0.185	0.130	0.125	0.150	0.205	0.110	0.095	0.180	0.250
15	0.110	0.140	0.17	0.390	0.120	0.125	0.200	0.390	0.080	0.155	0.185	0.435	0.100	0.085	0.230	0.500
20	0.105	0.180	0.28	0.630	0.095	0.155	0.275	0.635	0.115	0.140	0.320	0.615	0.135	0.165	0.315	0.705
25	0.125	0.235	0.40	0.840	0.120	0.270	0.485	0.865	0.090	0.185	0.485	0.875	0.160	0.230	0.455	0.875
30	0.100	0.285	0.57	0.985	0.120	0.345	0.610	0.975	0.130	0.300	0.635	0.975	0.175	0.380	0.655	0.990

Table C12. Power of trend detection for changes in fall NO₃ for annual surveys of 30 lakes.

Years	[1-0]				[(1-0),(2-3)]				[(1-0),(1-3)]				[(1-0),(2-5)]			
	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$	$\delta=0.20$	$\delta=0.40$	$\delta=0.60$	$\delta=0.80$
5	0.190	0.240	0.190	0.175	0.175	0.145	0.175	0.175	0.175	0.220	0.180	0.155	0.150	0.135	0.145	0.160
10	0.160	0.180	0.175	0.205	0.125	0.140	0.165	0.225	0.085	0.135	0.175	0.185	0.130	0.150	0.190	0.235
15	0.140	0.180	0.165	0.390	0.155	0.105	0.255	0.370	0.160	0.140	0.180	0.430	0.130	0.160	0.265	0.435
20	0.100	0.215	0.355	0.680	0.140	0.165	0.305	0.670	0.120	0.160	0.335	0.650	0.120	0.185	0.295	0.765
25	0.115	0.215	0.500	0.905	0.145	0.270	0.540	0.890	0.150	0.225	0.535	0.835	0.135	0.215	0.565	0.905
30	0.140	0.260	0.665	0.975	0.165	0.270	0.680	0.985	0.150	0.375	0.740	0.980	0.120	0.315	0.735	0.995

Table C13. Power of trend detection for changes in fall SO₄ for annual surveys over 10 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.100	0.190	0.365	0.130	0.170	0.330	0.095	0.235	0.315	0.100	0.230	0.355
10	0.210	0.375	0.630	0.290	0.360	0.625	0.245	0.390	0.660	0.200	0.450	0.660
15	0.295	0.500	0.745	0.235	0.505	0.695	0.240	0.515	0.780	0.255	0.490	0.750
20	0.285	0.470	0.730	0.285	0.515	0.675	0.295	0.495	0.790	0.325	0.485	0.810
25	0.300	0.510	0.725	0.275	0.495	0.765	0.335	0.550	0.825	0.275	0.525	0.765
30	0.295	0.555	0.760	0.265	0.530	0.760	0.295	0.590	0.800	0.325	0.510	0.805
35	0.275	0.585	0.785	0.340	0.630	0.830	0.320	0.575	0.810	0.365	0.560	0.825
40	0.365	0.540	0.830	0.300	0.520	0.820	0.355	0.520	0.820	0.370	0.565	0.810
45	0.300	0.570	0.800	0.335	0.500	0.805	0.370	0.495	0.830	0.330	0.590	0.790
50	0.340	0.550	0.870	0.380	0.515	0.810	0.365	0.595	0.825	0.325	0.555	0.795

Table C14. Power of trend detection for changes in fall SO_4 for annual surveys over 30 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.120	0.110	0.180	0.070	0.135	0.195	0.045	0.120	0.175	0.060	0.100	0.190
10	0.130	0.205	0.415	0.110	0.270	0.440	0.170	0.325	0.505	0.145	0.345	0.585
15	0.145	0.280	0.500	0.235	0.455	0.725	0.220	0.395	0.730	0.270	0.510	0.735
20	0.160	0.365	0.560	0.290	0.520	0.765	0.280	0.480	0.750	0.335	0.605	0.810
25	0.190	0.445	0.685	0.310	0.555	0.815	0.310	0.555	0.795	0.345	0.555	0.875
30	0.265	0.415	0.765	0.330	0.630	0.850	0.320	0.585	0.920	0.420	0.675	0.925
35	0.290	0.500	0.795	0.360	0.620	0.925	0.340	0.655	0.895	0.435	0.695	0.960
40	0.295	0.540	0.830	0.370	0.655	0.955	0.360	0.635	0.930	0.445	0.715	0.965
45	0.320	0.585	0.810	0.455	0.715	0.950	0.405	0.685	0.945	0.455	0.740	0.950
50	0.330	0.620	0.880	0.450	0.725	0.970	0.465	0.740	0.950	0.480	0.770	0.960

Table C15. Power of trend detection for changes in fall SO_4 for annual surveys of 25 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.160	0.215	0.170	0.225	0.185	0.145	0.170	0.170	0.210	0.165	0.140	0.195
10	0.105	0.130	0.210	0.130	0.235	0.230	0.115	0.210	0.235	0.145	0.185	0.290
15	0.200	0.275	0.365	0.185	0.275	0.440	0.145	0.285	0.405	0.175	0.250	0.460
20	0.200	0.300	0.465	0.170	0.415	0.655	0.210	0.385	0.655	0.300	0.410	0.625
25	0.210	0.340	0.635	0.245	0.480	0.765	0.280	0.455	0.790	0.300	0.545	0.805
30	0.210	0.380	0.625	0.285	0.545	0.785	0.305	0.555	0.805	0.320	0.620	0.825

Table C16. Power of trend detection for changes in fall SO₄ for annual surveys of 30 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.150	0.175	0.155	0.205	0.225	0.215	0.175	0.220	0.210	0.135	0.175	0.160
10	0.155	0.225	0.180	0.130	0.160	0.265	0.145	0.210	0.245	0.190	0.190	0.320
15	0.150	0.200	0.355	0.195	0.275	0.485	0.210	0.275	0.355	0.160	0.305	0.495
20	0.190	0.350	0.570	0.235	0.415	0.655	0.190	0.475	0.630	0.325	0.435	0.725
25	0.245	0.395	0.710	0.260	0.620	0.770	0.235	0.550	0.755	0.355	0.575	0.840
30	0.300	0.440	0.685	0.330	0.590	0.860	0.355	0.670	0.865	0.355	0.685	0.890

Table C17. Power of trend detection for changes in fall PN for annual surveys over 10 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.065	0.115	0.220	0.085	0.080	0.145	0.065	0.120	0.190	0.085	0.150	0.180
10	0.130	0.315	0.400	0.180	0.310	0.500	0.155	0.245	0.390	0.175	0.300	0.480
15	0.220	0.305	0.555	0.230	0.390	0.595	0.200	0.295	0.520	0.220	0.355	0.540
20	0.170	0.330	0.595	0.220	0.370	0.560	0.190	0.360	0.630	0.220	0.360	0.560
25	0.220	0.390	0.615	0.225	0.345	0.555	0.235	0.355	0.605	0.200	0.365	0.545
30	0.215	0.405	0.650	0.215	0.405	0.620	0.290	0.395	0.585	0.300	0.380	0.620
35	0.230	0.415	0.640	0.180	0.385	0.595	0.210	0.390	0.680	0.235	0.400	0.600
40	0.225	0.430	0.625	0.270	0.435	0.555	0.290	0.440	0.640	0.285	0.410	0.640
45	0.280	0.425	0.605	0.230	0.465	0.630	0.235	0.430	0.635	0.295	0.390	0.625
50	0.290	0.435	0.635	0.245	0.435	0.645	0.260	0.460	0.635	0.265	0.430	0.665

Table C18. Power of trend detection for changes in fall PN for annual surveys over 30 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.075	0.125	0.200	0.070	0.110	0.165	0.085	0.115	0.205	0.080	0.125	0.255
10	0.175	0.280	0.365	0.130	0.345	0.575	0.195	0.370	0.600	0.200	0.485	0.645
15	0.205	0.375	0.595	0.200	0.480	0.755	0.210	0.495	0.750	0.275	0.450	0.800
20	0.295	0.445	0.650	0.355	0.465	0.770	0.280	0.490	0.795	0.280	0.570	0.845
25	0.245	0.435	0.725	0.305	0.580	0.840	0.330	0.585	0.840	0.360	0.630	0.870
30	0.260	0.570	0.745	0.345	0.630	0.860	0.310	0.600	0.885	0.320	0.670	0.840
35	0.330	0.445	0.805	0.275	0.590	0.905	0.350	0.665	0.890	0.345	0.645	0.835
40	0.340	0.525	0.810	0.320	0.675	0.900	0.440	0.660	0.900	0.385	0.700	0.920
45	0.305	0.610	0.830	0.390	0.700	0.930	0.360	0.625	0.930	0.425	0.700	0.935
50	0.305	0.605	0.830	0.365	0.690	0.915	0.390	0.655	0.940	0.340	0.760	0.930

Table C19. Power of trend detection for changes in fall PN for annual surveys of 25 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.210	0.175	0.170	0.190	0.135	0.195	0.170	0.155	0.165	0.155	0.135	0.200
10	0.130	0.200	0.145	0.150	0.120	0.150	0.115	0.140	0.180	0.115	0.155	0.180
15	0.135	0.165	0.345	0.180	0.205	0.320	0.165	0.205	0.375	0.165	0.280	0.405
20	0.185	0.260	0.500	0.190	0.330	0.530	0.195	0.315	0.515	0.275	0.340	0.560
25	0.200	0.385	0.645	0.225	0.350	0.690	0.245	0.455	0.675	0.250	0.455	0.805
30	0.220	0.445	0.675	0.300	0.550	0.790	0.300	0.510	0.850	0.360	0.565	0.840

Table C20. Power of trend detection for changes in fall PN for annual surveys of 30 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.165	0.175	0.225	0.180	0.180	0.240	0.210	0.200	0.140	0.095	0.195	0.160
10	0.135	0.160	0.220	0.170	0.175	0.225	0.140	0.175	0.205	0.165	0.145	0.220
15	0.125	0.220	0.300	0.180	0.235	0.335	0.145	0.285	0.355	0.170	0.260	0.365
20	0.200	0.325	0.495	0.150	0.300	0.465	0.225	0.345	0.585	0.215	0.380	0.555
25	0.215	0.500	0.670	0.265	0.530	0.780	0.240	0.475	0.790	0.295	0.495	0.745
30	0.255	0.545	0.690	0.295	0.650	0.890	0.300	0.570	0.905	0.315	0.610	0.880

Table C21. Power of trend detection for changes in fall PP for annual surveys over 10 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.060	0.115	0.150	0.060	0.125	0.140	0.045	0.110	0.125	0.090	0.145	0.150
10	0.130	0.175	0.345	0.165	0.290	0.320	0.160	0.195	0.325	0.135	0.240	0.260
15	0.180	0.290	0.355	0.130	0.290	0.315	0.130	0.310	0.330	0.190	0.270	0.355
20	0.185	0.205	0.300	0.175	0.245	0.365	0.235	0.225	0.380	0.180	0.265	0.370
25	0.140	0.225	0.410	0.240	0.230	0.390	0.150	0.240	0.370	0.145	0.250	0.330
30	0.155	0.275	0.355	0.190	0.295	0.305	0.235	0.270	0.360	0.240	0.220	0.430
35	0.160	0.295	0.425	0.175	0.310	0.425	0.180	0.250	0.400	0.180	0.250	0.400
40	0.170	0.265	0.375	0.180	0.265	0.390	0.195	0.285	0.390	0.195	0.225	0.435
45	0.185	0.260	0.415	0.205	0.255	0.370	0.180	0.285	0.355	0.215	0.240	0.435
50	0.150	0.205	0.380	0.215	0.270	0.415	0.160	0.330	0.440	0.200	0.280	0.420

Table C22. Power of trend detection for changes in fall PP for annual surveys over 30 years.

Lakes	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.080	0.175	0.260	0.050	0.165	0.310	0.070	0.175	0.380	0.080	0.200	0.330
10	0.170	0.375	0.545	0.195	0.340	0.600	0.195	0.405	0.600	0.160	0.445	0.635
15	0.230	0.405	0.700	0.270	0.405	0.685	0.245	0.450	0.645	0.220	0.405	0.715
20	0.210	0.385	0.625	0.215	0.400	0.700	0.260	0.470	0.685	0.240	0.485	0.690
25	0.220	0.460	0.690	0.220	0.485	0.755	0.300	0.470	0.675	0.255	0.480	0.700
30	0.245	0.475	0.690	0.280	0.445	0.740	0.250	0.450	0.780	0.235	0.505	0.675
35	0.255	0.505	0.715	0.235	0.450	0.720	0.230	0.500	0.725	0.240	0.455	0.700
40	0.305	0.450	0.780	0.220	0.480	0.775	0.330	0.440	0.740	0.220	0.545	0.740
45	0.260	0.535	0.745	0.265	0.450	0.795	0.245	0.490	0.780	0.280	0.510	0.785
50	0.285	0.480	0.725	0.270	0.495	0.710	0.285	0.510	0.740	0.270	0.550	0.750

Table C23. Power of trend detection for changes in fall PP for annual surveys of 25 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.235	0.210	0.180	0.185	0.155	0.210	0.185	0.160	0.185	0.155	0.155	0.195
10	0.110	0.180	0.125	0.150	0.120	0.130	0.140	0.130	0.155	0.120	0.120	0.140
15	0.120	0.140	0.265	0.180	0.160	0.200	0.135	0.165	0.285	0.130	0.185	0.275
20	0.145	0.210	0.335	0.145	0.230	0.310	0.130	0.255	0.350	0.205	0.230	0.355
25	0.175	0.280	0.525	0.175	0.280	0.530	0.220	0.345	0.525	0.195	0.315	0.595
30	0.195	0.385	0.715	0.245	0.440	0.635	0.300	0.435	0.700	0.290	0.465	0.745

Table C24. Power of trend detection for changes in fall PP for annual surveys of 30 lakes.

Years	[1-0]			[(1-0),(2-3)]			[(1-0),(1-3)]			[(1-0),(2-5)]		
	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$	$\delta=0.20$	$\delta=0.30$	$\delta=0.40$
5	0.170	0.190	0.215	0.175	0.200	0.215	0.220	0.225	0.150	0.105	0.175	0.150
10	0.135	0.135	0.145	0.175	0.155	0.200	0.140	0.170	0.180	0.125	0.105	0.165
15	0.110	0.215	0.220	0.170	0.195	0.250	0.115	0.225	0.215	0.150	0.165	0.235
20	0.175	0.255	0.375	0.130	0.215	0.315	0.150	0.260	0.360	0.165	0.225	0.370
25	0.210	0.395	0.565	0.175	0.360	0.535	0.175	0.320	0.550	0.190	0.340	0.515
30	0.230	0.490	0.650	0.235	0.485	0.695	0.210	0.495	0.680	0.235	0.430	0.735

The Department of the Interior protects and manages the nation's natural resources and cultural heritage; provides scientific and other information about those resources; and honors its special responsibilities to American Indians, Alaska Natives, and affiliated Island Communities.

NPS 963/116860, September 2012

National Park Service
U.S. Department of the Interior



Natural Resource Stewardship and Science

1201 Oakridge Drive, Suite 150
Fort Collins, CO 80525

www.nature.nps.gov

EXPERIENCE YOUR AMERICA™