Regional trends in fish mean length at age: components of variance and the statistical power to detect trends

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Abstract: We examined statewide time series (1940s–2002) of mean length at ages 2, 3, and 4 for seven fish species sampled from Michigan and Wisconsin inland lakes for temporal trends. We used a components of variance approach to examine how total variation in mean length at age was partitioned into lake-to-lake, coherent temporal, ephemeral temporal, trend, and residual variation. Using these estimated variance components, we simulated the effects of different variance structures on the power to detect trends in mean length at age. Of the 42 data sets examined, only four demonstrated significant regional (statewide) trends: age 4 largemouth bass (*Micropterus salmoides*) from Wisconsin lakes increased about 0.7 mm·year^{-1} in mean length at age, and ages 2, 3, and 4 walleye (*Sander vitreus*) from Wisconsin lakes decreased between 0.5 and 0.9 mm·year^{-1} in mean length at age. The structure of variation differed substantially among data sets, and these differences strongly affected the power to detect trends. Of particular note was that even modest levels of coherent temporal variation led to substantial decreases in power for detecting trends. To maximize trend detection capabilities, fisheries management agencies should consider variance structures prior to choosing indices for monitoring and realize that trend detection capabilities are species- and region-specific.

Résumé : Afin de déceler des tendances temporelles, nous avons examiné des séries chronologiques (années 1940 à 2002) de longueurs moyennes aux âges 2, 3 et 4 de sept espèces de poissons échantillonnés dans les lacs intérieurs sur l'ensemble du territoire des états du Michigan et du Wisconsin. Nous avons utilisé la méthode des composantes de la variance pour déterminer de quelle manière la variation totale des longueurs moyennes en fonction de l'âge peut se répartir en diverses composantes, soit en variation entre les lacs, en variations temporelles cohérente et éphémère, en variation reliée aux tendances et en variation résiduelle. À l'aide de ces composantes estimées de la variance, nous avons simulé les effets de diverses structures de la variance sur la puissance de détection des tendances dans les longueurs moyennes en fonction de l'âge. Des 42 séries de données examinées, seules quatre montrent des tendances régionales (à l'échelle de l'état) significatives: les achigans à grande bouche (*Micropterus salmoides*) d'âge 4 des lacs du Wisconsin ont augmenté d'environ 0,7 mm·année^{-1} en longueur moyenne en fonction de l'âge, alors que les dorés jaune (*Sander vitreus*) d'âges 2, 3 et 4 des lacs du Wisconsin ont diminué de 0,5 à 0,9 mm·année^{-1} en longueur moyenne en fonction de l'âge. La structure de la variation diffère considérablement entre les banques de données et ces différences affectent fortement la puissance de détection des tendances. En particulier, même des niveaux modestes de variation temporelle cohérente font diminuer considérablement la puissance de détection des tendances. Afin de maximiser leurs capacités de détection des tendances, les agences de gestion des pêches devraient examiner les structures de variance avant de choisir des indices de surveillance; elles devraient aussi se rendre compte que les capacités de détection des tendances varient de façon spécifique en fonction des espèces et des régions.

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Introduction

Knowledge of trends in fish growth rates is important ecologically, as growth rates influence ecological interactions and population dynamics and are often used along with recruitment and mortality information to assist management decisions (Trippel 1993). Furthermore, growth rates are influenced by environmental conditions and can represent an integrative measure of conditions experienced by a fish over its lifetime. Consequently, one goal of many fishery monitoring programs is to determine whether growth of fish populations (e.g., as indicated by mean size at age) is changing

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with time and if so, whether such changes are consistent across species and across systems.

Factors that lead to changes in fish growth over time and space include both biotic factors such as differences in prey abundance and fish density (i.e., density-dependent growth; Claramunt and Wahl 2000; Quist et al. 2003; Sass et al. 2004) and abiotic factors such as differences in water temperature and lake morphometry characteristics (e.g., lake area; Claramunt and Wahl 2000; Quist et al. 2003). Many of these factors change temporally (e.g., yearly variation in temperature and regional management plans) and may lead to regional temporal trends in growth rates. Others vary spatially; for example, density-dependent growth of walleye in northern Wisconsin was shown to be density dependent within individual lakes; however, it was noted that the degree of density dependence among lakes differed spatially likely because of lake-specific properties, such as differences in productivity, prey species composition and abundance, and management regime (Sass et al. 2004).

Most work on evaluating trends in fish growth has focused on individual populations (e.g., Reckahn 1986; Szalai et al. 2003; He and Bence 2007). Although, there have been some regional evaluations of trends in fish demographics (McDonough and Buchanan 1991; Beard and Kampa 1999; Grant et al. 2004), the majority of aquatic work evaluating trends has emphasized single systems and water quality across rivers (Antonopoulos et al. 2001), lakes (Jassby et al. 1999, but see Urquhart et al. 1998 and Larsen et al. 1995), and seas (Sandén and Håkansson 1996). Although investigations into temporal trends within individual systems provide valuable information, the ability to detect regional (e.g., statewide) temporal trends is crucial for the evaluation of many management actions and to examine responses to natural or anthropogenic perturbations. Furthermore, the early detection of regional changes is important in many cases to allow time for managers and policy-makers to respond and take appropriate action (Vaughan et al. 2001). This said, detection of regional trends in fish growth (or other parameters) is challenging because available data are often limited, and regional trends can become obscured by large amounts of temporal variation common to the region or unique to particular populations within a region.

We provide one approach to evaluating regional trends in fish growth and use the estimated structures of variance to evaluate the statistical power of different sampling designs for detecting regional trends in fish growth. Mean size at age data are the most frequently available information on fish growth and provide an integrative measure of fish growth over the fish lifespan up to the age it was collected. In the data sets we considered, the same lake was only infrequently sampled in two sequential years, and data were commonly missing for one or more ages. Consequently, we analyzed mean size at age separately for each age as an index of growth. We use these results to provide insight into design and feasibility of reliable monitoring programs.

Trends and components of variance

A components of variance approach has been advocated to address the issue of variability in ecological data when evaluating regional temporal trends and monitoring of ecological systems (Urquhart et al. 1998; Larsen et al. 2001; Kincaid et al. 2004). Under this framework, total variance is partitioned into four components, including (*i*) site-to-site (spatial) variation, (*ii*) coherent (year-to-year) variation affecting all sites (e.g., lakes) in a similar manner, (*iii*) ephemeral temporal variation (e.g., site × year interaction) corresponding to independent yearly variation at each site, and (*iv*) residual variation (Larsen et al. 2001; Kincaid et al. 2004). A fifth component can be included in this framework in which each site has its own trend (i.e., trend variation: allowing the slope of the response variable versus time at each site to be a draw from a distribution and estimate the variance of the distribution of slopes; VanLeeuwen et al. 1996).

Although the total variance of the data is one of the primary factors affecting the ability to detect trends (Stow et al. 1998), the structure of that variance is far more important; likewise the temporal sampling design can be more important than total variation. Power analysis is a useful tool for evaluating the performance of ecological monitoring programs (Peterman 1990; Fairweather 1991; Hatch 2003) and in particular for investigating how specific variance components affect the power to detect trends for a given sampling design. Ideally, a monitoring program should have high statistical power, or the ability to detect a specific deviation from a null hypothesis.

Random effects models have been used to partition variability in fish growth data (e.g., changes in annual increment in length, Osenberg et al. 1988). However, to our knowledge, a components of variance approach has not been applied to mean length at age or other fish growth data within the context of trend detection over a large spatial region, even though fisheries agencies are collecting length at age data through time to monitor regions of lakes and streams (e.g., Hayes et al. 2003). The specific objectives of this study were to (*i*) determine if trends are evident in mean length at age for seven fish species in Michigan and Wisconsin inland lakes, (*ii*) quantify the components of variance for mean length at age, and (*iii*) perform power analyses to investigate the effects of the different components of variance on the statistical power to detect trends and to evaluate alternative sampling designs.

Materials and methods

Data sets

We obtained mean length at age data for seven fish species collected during survey sampling of inland lakes conducted by the Fisheries Division of the Michigan Department of Natural Resources (MIDNR) and the Wisconsin Department of Natural Resources. We included bluegill (*Lepomis macrochirus*), pumpkinseed (*Lepomis gibbosus*), largemouth bass (*Micropterus salmoides*), smallmouth bass (*Micropterus dolomieu*), yellow perch (*Perca flavescens*), walleye (*Sander vitreus*), and northern pike (*Esox lucius*) because of their prevalence in the historical data. In each lake survey, length at age was measured; mean length at age is available in the long-term data set by species and age. The corresponding number of fish that contributed to the mean was also recorded along with the day of year that sampling occurred. We restricted our analyses to mean length at ages 2, 3, and 4 for each species because the reliability of fish

Table 1. Fish species, age, sample size (*N*, number of observations used in the analyses), gear type used to collect fish, and sampling years used in the trend analysis for Michigan and Wisconsin inland lakes.

	N		Gear type		Sampling years	
Species (age)	Michigan	Wisconsin	Michigan	Wisconsin	Michigan	Wisconsin
BLG (2)	261	162	Electrofisher	Electrofisher	1961–2002	1959–2003
BLG (3)	265	216	Electrofisher	Electrofisher	1962–2002	1958–2003
BLG (4)	261	245	Electrofisher	Electrofisher	1963–2002	1958–2003
PSF (2)	51	66	Trap net	Electrofisher	1960–2002	1959–2003
PSF (3)	120	132	Trap net	Electrofisher	1960–2003	1959–1992
PSF (4)	143	146	Trap net	Electrofisher	1958–2003	1959–1992
LMB (2)	277	227	Electrofisher	Electrofisher	1961–2002	1958–2003
LMB (3)	275	285	Electrofisher	Electrofisher	1963–2002	1959–2003
LMB (4)	243	273	Electrofisher	Electrofisher	1963–2002	1959–2002
SMB (2)	93	52	Electrofisher	Electrofisher	1963–2001	1957–2003
SMB (3)	74	47	Electrofisher	Electrofisher	1963–2001	1957–2003
SMB (4)	61	44	Electrofisher	Electrofisher	1963–1999	1956–2003
YEP (2)	266	167	Electrofisher	Electrofisher	1961–2002	1958–2003
YEP (3)	229	203	Electrofisher	Electrofisher	1961–2002	1958–2003
YEP (4)	185	187	Electrofisher	Electrofisher	1961–2002	1958–2003
NOP (2)	157	166	Fyke net	Fyke net	1960–2002	1947–2002
NOP (3)	161	176	Fyke net	Fyke net	1957–2002	1947–2002
NOP (4)	151	183	Fyke net	Fyke net	1957–2002	1947–2002
WAE (2)	236	303	Electrofisher	Fyke net	1967–2002	1946–2001
WAE (3)	210	401	Electrofisher	Fyke net	1967–2002	1946–2001
WAE (4)	176	434	Electrofisher	Fyke net	1967–2002	1946–2001

Note: BLG, bluegill (*Lepomis macrochirus*); PSF, pumpkinseed (*Lepomis gibbosus*); LMB, largemouth bass (*Micropterus salmoides*); SMB, smallmouth bass (*Micropterus dolomieu*); YEP, yellow perch (*Perca flavescens*); NOP, northern pike (*Esox lucius*); WAE, walleye (*Sander vitreus*).

ageing decreases with increasing age (Ricker 1975) and because these ages had adequate sample sizes.

Mean length at age time series were available beginning in the early 1960s and continuing to the early 2000s for fish collected in Michigan and from the late 1940s or late 1950s to the early 2000s for fish collected in Wisconsin (Table 1). Fish were collected using a variety of gear types over the time series. Thus, in an effort to reduce potential biases introduced by using different sampling gear, we only retained fish collected using the same gear type in the analyses for each species, age, and state combination (Table 1). For nets, however, (e.g., trap nets and fyke nets) the mesh size was not recorded over time; thus we could not control for any potential changes in mesh size. Historically, fish were not sampled in a truly random design by the state agencies. However, the fish growth surveys used in this analysis represent a large sample of public lakes broadly distributed throughout both states, thus reducing the likelihood of substantial bias.

Temporal trend statistical analysis

A mixed model was used to assess the presence of regional (statewide) linear trends in mean length at age for each species, similar to that suggested by Piepho and Ogutu (2002). Although we restricted our analysis to the investigation of linear trends, if a monotonic increase or decrease is present, then a linear trend will be present (Urquhart and Kincaid 1999). Each state and species–age data set was analyzed separately because differences in sampling methodologies between agencies could influence variance components and possibly the overall trends. Each data point (mean length at age) was weighted by the number of fish that contributed to each mean for each lake. To account for potential variation introduced by fish being sampled during different times of the year (i.e., seasonal trends in mean length at age), seasonal trends were examined prior to the interannual analysis by fitting linear and quadratic least-squares regression models (Grant et al. 2004). For each species–age combination with a significant seasonal trend, the regression equation was used to adjust mean length at age to the median sample date.

The mixed model used for the analyses was

$$(1) \qquad y_{ij} = \mu + a_i + y(\lambda + t_i) + b_j + c_{ij} + e_{ij}$$

where Y_{ij} is the mean length at age for lake i in year j, and μ and λ are the fixed intercept and slope (fixed regional trend), respectively. The random effect a_i is a random effect for lake i, representing lake-to-lake variability, independent and identically distributed (iid) as $N(\sigma_a^2)$; b_j is a random effect for the jth year (coherent temporal variability), iid as $N(0, \sigma_b^2)$; t_i is a random effect for the trend for lake i, iid as $N(0, \sigma_t^2)$; c_{ij} is the lake × year interaction (ephemeral temporal variability), iid as $N(0, \sigma_c^2)$; and e_{ij} is the unexplained error (residual error), independent as $N(0, \sigma_e^2/n_{ij})$. Note that e_{ij} represents sampling error that influences the observed mean length at age, and this variance is assumed to be inversely related to sample size (n_{ij}). In practice, this means that the model was fit by weighting observations (means for a year and age) by their sample sizes, and σ_e^2 should be viewed as describing variation among individual fish. The year covariate (y) is the *j*th year minus the mean year used in the analysis. This standardization of year was performed to provide numerical stability.

We estimated variance components using restricted maximum likelihood and *P* values using a likelihood ratio test (Self and Liang 1987; Littell et al. 1996). We considered all analyses significant at $P < 0.05$. Because we could not estimate the lake × year interaction effect for most data sets (e.g., the data sets did not contain sufficient data on lakes sampled multiple times within a year or overall sample size was small), we used a simpler model to examine temporal trends that excludes the estimation of the variance due to lake × year interaction. In this case, the variance due to the lake × year interaction is contained within the residual error term. Not estimating this parameter, however, does not affect the estimate of the slope.

Power analysis

We investigated the extent to which the following factors affected the ability to detect a trend: (1) increasing trend magnitude (λ ranged from –0.5 to 2.0 mm·year^{-1}), (2) increasing number of fish sampled per lake (ranging from 5 to 30 fish·lake^{-1}), (3) increasing the number of lakes sampled per year (ranging from 10 to 40 lakes·year^{-1}), (4) decreasing lake effect variance, and (5) sampling from a population of 50 or 1000 lakes. We address factor 1 to provide information on the effects of trend magnitude on power; factors 2 and 3 are addressed because the number of fish and lakes sampled is an important consideration for sampling designs with respect to allocating personnel and fiscal time and money resources. We address factor 4 to understand how power would increase if lake-to-lake variance was reduced, for example, by using a lake classification scheme. To this end, we reduced lake-to-lake variance by 50% and then reduced it to zero to explore the effects of a large reduction in lake-to-lake variance. Finally, we examined factor 5 to examine how the proportion of lakes sampled each year influences statistical power. For simulations for which sampling from a population of 50 or 1000 lakes did not change the general patterns observed, we report only those results for sampling from a 50-lake population, unless otherwise stated.

We used a simulation approach to examine the statistical power to detect temporal trends using the variance components estimated from eq. 1. For each simulation, 1000 data sets were generated containing species-specific mean length at age data for a population of lakes (50 or 1000 lakes; see below) over 25 years. First, a true mean length at age for each lake in the population was generated over the 25-year time period. A trend of known magnitude (e.g., a decease of 1 mm·year^{-1}) was also incorporated into the data set. Using the true mean lengths at ages for each lake, an observed mean length at age was then generated for each lake by randomly generating lengths for a prespecified number of fish (ranging from 5 to 30) for each of the lakes from a normal distribution with a mean equal to the true mean and variance equal to the estimated residual (sampling) variance from eq. 1. From these 1000 data sets, a user-specified number of lakes (ranging from 10 to 40) were then randomly sampled from the population of 50 or 1000 lakes each year. When the number of fish sampled per lake was held constant, we used the mean number of fish sampled per age class from our surveys ($\bar{x} = 10$). Thirty lakes sampled per year was used as a realistic number of lakes that could be sampled per year by a management agency when the number of lakes sampled per year was held constant (K. Wehrly, Fisheries Division, MIDNR, Institute of Fisheries Research, 1109 North University Avenue, Ann Arbor, MI 48109, USA, personal communication). Lakes were sampled without replacement within a year, but all lakes were available for selection each year. Data were analyzed for different sampling durations from 5 up to 25 years and analyzed for the presence of a trend. The model specified in eq. 1 was used to test the null hypothesis that $\hat{\lambda} = 0$ for each data set, and the test statistic was calculated and compared with a critical value ($\alpha = 0.05$). Because the data generated depict a situation in which we know the null hypothesis is false (i.e., a trend of known magnitude was incorporated into the data), power was estimated as the percentage of trials (out of 1000) that rejected the null hypothesis.

Results

Temporal trend

Not all data sets contained enough information to fit the model to evaluate temporal trends. Of 42 data sets examined (7 species × 3 ages × 2 states), we were able to examine temporal trends for only 26 data sets (Table 2). Of the 26 analyses, only four demonstrated significant temporal trends. The slope estimate for age 4 largemouth bass from Wisconsin lakes was significant, with an increase of about 0.7 mm·year^{-1} in mean length at age. Ages 2, 3, and 4 walleye from Wisconsin lakes showed a negative trend, decreasing between 0.5 and 0.9 mm·year^{-1} in mean length at age (Table 2). For all other analyses, estimates of the slope for the fixed regional trend had absolute values of 0.43 mm·year^{-1} or less, which were not significantly different from zero at our specified alpha level ($P > 0.05$).

Variance components

We could not estimate the lake × year interaction effect for 20 of 26 of the data sets used in trend estimation. For the data sets where estimation was possible, the structure of variation differed substantially among data sets (Table 3; Fig. 1). Mean residual variation $\hat{\sigma}_e^2$ was 54% and ranged from 18.1% to 75.7% of the total variation. Mean ephemeral temporal variation ($\hat{\sigma}_c^2$) was 17.2% and ranged from 4.9% to 30.6% of the total variation. The mean percentage of total variation attributed to coherent temporal variation $\hat{\sigma}_b^2$ was 3.5% and ranged from 0.5% to 8.7%. The mean percentage of total variation attributed to lake-to-lake differences $\hat{\sigma}_a^2$ was 25.4% and ranged from 5.5% to 50.5%. The mean percentage of the total variation due to trend variation $\hat{\sigma}_t^2$ was small (mean = 0.1%), ranging from 0.01% to 0.24%.

Power analysis

We investigated the effects of variance structures on statistical power by contrasting two carefully chosen data sets, which had strikingly different variance structures, namely age 4 walleye sampled in Michigan and Wisconsin (Fig. 1). Because the slope estimates for the significant analyses of temporal trends ranged from –0.5 to –0.9, we used $\lambda = -1.0$ mm·year^{-1} for simulations in

Table 2. Parameter estimates for the fixed effect of sampling year (fixed regional trend (mm·year^{-1}), $\hat{\lambda}$) followed by standard error (SE) in parentheses, *F* value, and *P* value for mean length at age of seven fish species in Michigan and Wisconsin inland lakes.

	$\hat{\lambda}$ (SE)		*F*		*P*	
Species (age)	Michigan	Wisconsin	Michigan	Wisconsin	Michigan	Wisconsin
BLG (2)	–0.176 (0.160)	NE	1.20	NE	0.282	NE
BLG (3)	–0.012 (0.173)	–0.425 (0.195)	0.01	4.73	0.944	0.118
BLG (4)	0.004 (0.198)	–0.413 (0.196)	0.00	4.43	0.983	0.059
PSF (2)	NE	NE	NE	NE	NE	NE
PSF (3)	–0.046 (0.262)	NE	0.03	NE	0.873	NE
PSF (4)	0.066 (0.237)	–0.381 (0.242)	0.08	2.48	0.788	0.176
LMB (2)	–0.221 (0.265)	NE	0.69	NE	0.412	NE
LMB (3)	–0.390 (0.267)	0.306 (0.314)	2.13	0.95	0.157	0.338
LMB (4)	–0.292 (0.285)	**0.672 (0.313)**	1.05	**4.59**	0.326	**0.045**
SMB (2)	–0.202 (0.425)	NE	0.23	NE	0.655	NE
SMB (3)	–0.392 (0.743)	NE	0.28	NE	0.626	NE
SMB (4)	NE	NE	NE	NE	NE	NE
YEP (2)	–0.077 (0.176)	NE	0.19	NE	0.665	NE
YEP (3)	–0.271 (0.210)	NE	1.69	NE	0.213	NE
YEP (4)	0.165 (0.260)	NE	0.40	NE	0.545	NE
NOP (2)	–0.430 (0.753)	NE	0.33	NE	0.577	NE
NOP (3)	NE	NE	NE	NE	NE	NE
NOP (4)	NE	–0.036 (0.435)	NE	0.01	NE	0.947
WAE (2)	0.096 (0.448)	**–0.917 (0.283)**	0.05	**10.52**	0.831	**0.002**
WAE (3)	0.074 (0.918)	**–0.530 (0.257)**	0.01	**4.26**	0.936	**0.042**
WAE (4)	0.138 (0.816)	**–0.676 (0.237)**	0.03	**8.13**	0.867	**0.005**

Note: Significant regional trends are shown in bold ($\alpha = 0.05$). BLG, bluegill (*Lepomis macrochirus*); PSF, pumpkinseed (*Lepomis gibbosus*); LMB, largemouth bass (*Micropterus salmoides*); SMB, smallmouth bass (*Micropterus dolomieu*); YEP, yellow perch (*Perca flavescens*); NOP, northern pike (*Esox lucius*); WAE, walleye (*Sander vitreus*); NE, not estimable.

Table 3. Estimated variance components followed by standard error in parentheses from a weighted mixed model examining mean length at age over time for Michigan and Wisconsin inland lakes.

Species (age)	Lake-to-lake ($\hat{\sigma}_a^2$)	Coherent temporal ($\hat{\sigma}_b^2$)	Ephemeral temporal ($\hat{\sigma}_c^2$)	Trend variation ($\hat{\sigma}_t^2$)	Residual error ($\hat{\sigma}_e^2$)
Michigan					
YEP (2)	59.1 (91.4)	**31.6 (23.5)**	**227.1 (100.4)**	0.4 (0.43)	**765.9 (200.4)**
LMB (3)	**240.9 (108.8)**	32.8 (40.1)	**455.4 (121.4)**	1.4 (1.1)	**1145.0 (261.0)**
WAE (3)	**1526.4 (368.8)**	95.5 (101.6)	**533.7 (168.8)**	**8.2 (4.7)**	**1238.8 (315.4)**
WAE (4)	**1531.8 (402.0)**	16.1 (88.4)	**928.4 (268.2)**	4.9 (4.2)	**549.9 (216.1)**
Wisconsin					
WAE (3)	**833.5 (139.9)**	**313.2 (179.1)**	**225.6 (63.9)**	0.4 (0.4)	**2230.9 (504.9)**
WAE (4)	**1001.8 (167.6)**	**260.7 (155.6)**	**319.3 (87.9)**	**0.8 (0.5)**	**4936.2 (1063.9)**

Note: Variance components significantly different from zero are shown in bold ($\alpha = 0.05$). YEP, yellow perch (*Perca flavescens*); LMB, largemouth bass (*Micropterus salmoides*); WAE, walleye (*Sander vitreus*).

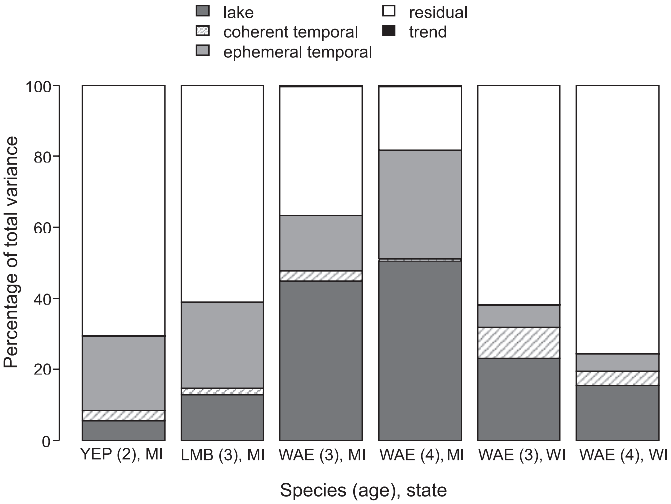
which λ was held constant. Trends less than this would likely not be considered biologically significant in the short term.

The power to detect trends in mean length at age increased, as expected, with increasing trend magnitude (Fig. 2). For example, after 15 years of sampling, the power to detect a trend increased from 0.2 to 1.0 as λ decreased from –0.5 to –2.0 mm·year^{-1} for age 4 walleye sampled from Michigan lakes. For age 4 walleye sampled from Wisconsin lakes, power also increased with trend magnitude, but power at a given number of years and trend magnitude was markedly lower in Wisconsin as compared with Michigan, demonstrating the influence of the different variance structures between states.

In an effort to visualize the trade-offs between sampling more fish per lake versus sampling more lakes per year, we plotted power curves for both Michigan and Wisconsin walleye across 10- and 25-year sampling periods (Fig. 3). For walleye sampled in Michigan, the greatest increase in power at 10 years of sampling was gained by increasing the number of lakes sampled each year, with only a slight gain in power achieved by increasing the number of fish sampled in each lake. For example, if 30 lakes were sampled per year, increasing the number of fish sampled from 5 to 30 increased power by only 0.05. In contrast, assuming 10 fish were sampled from each lake, increasing the number of lakes sampled from 10 to 40 increased power by 0.3. A similar pattern was observed at 25 years; however, relatively high power (ranging from 0.85 to 1.0) was obtained regardless of the number of lakes or fish sampled (Fig. 3).

A different pattern was observed for walleye sampled from Wisconsin (Fig. 3). At 10 and 25 years of sampling, al-

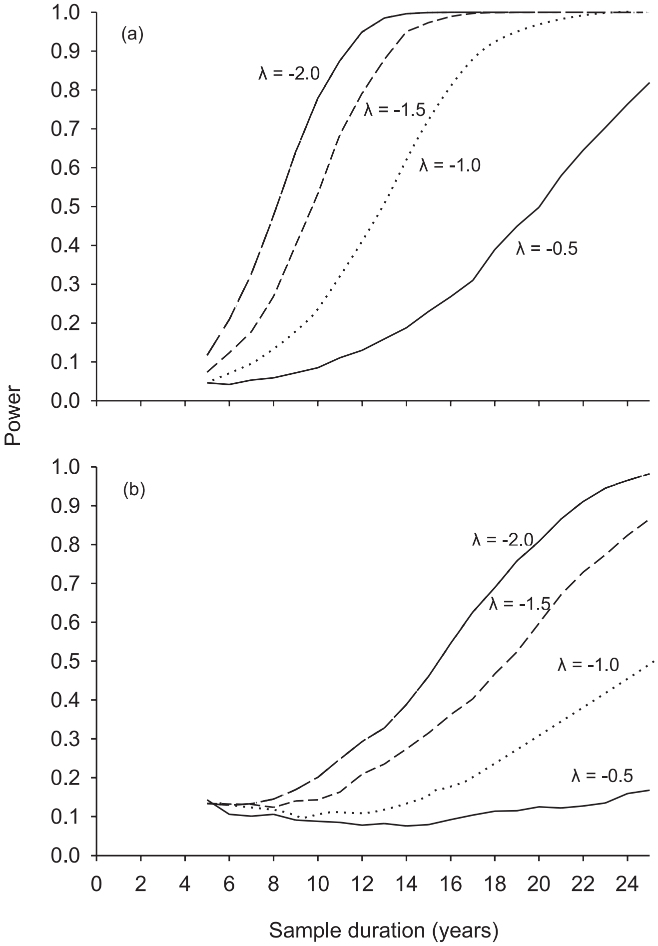
Fig. 1. Estimated percentage of total variation attributed to lake, coherent temporal, ephemeral temporal, trend variation, and residual variance. Estimates are from a mixed model for mean length at age versus time for six species–age combinations of fish from Michigan (MI) and Wisconsin (WI) inland lakes. YEP, yellow perch (*Perca flavescens*); LMB, largemouth bass (*Micropterus salmoides*); WAE, walleye (*Sander vitreus*). Note that trend variation is a very small percentage of the total variation and is only visible at the top of the bars for age 3 and 4 walleye from Michigan.



though increasing the number of lakes sampled each year from 10 to 20 increased power, power leveled off and remained relatively low even as the number of lakes increased from 20 to 40. Increasing the number of fish sampled from each lake did increase power; however, this increase was quite small. These patterns reflect the influence on the larger coherent temporal variance component in the Wisconsin data set.

Decreasing lake-to-lake variance did not have a noticeable effect on power for either walleye sampled in Michigan or Wisconsin when 60% of the total population of lakes was sampled each year (sampling 30 out of 50 lakes each year). The 60% sampling rate led to many revisits, thus letting the statistical analysis estimate and remove the lake effect from the trend detection. Power remained similar at all sampling durations (Fig. 4), but was consistently higher for Michigan compared with Wisconsin lakes, again reflecting the larger coherent temporal variance in the Wisconsin analysis. Under the scenario in which 3% of the lakes were sampled each year (sampling 30 out of 1000 lakes each year), decreasing lake-to-lake variance resulted in an increase in power for walleye sampled in Michigan, where lake-to-lake variance composed 51% of the total variance; however, this pattern of increasing power with decreasing lake-to-lake variance was not observed with the walleye sampled in Wisconsin lakes, where lake-to-lake variance was smaller, composing 15% of the total variance (Fig. 4). Furthermore, when sampling a small percentage (e.g., 3%) of the population of lakes, some models were not estimable over short sampling durations (<10 years) because there were not sufficient data on individual lakes sampled repeatedly over time. Thus, power estimates reported for sampling from the 1000 lake scenario are only for models that were estimable (i.e., the number of trials was <1000).

Fig. 2. Power curves for detecting temporal trends in mean length at age with increasing trend magnitude (λ = mm·year^{-1}) for age 4 walleye (*Sander vitreus*) in Michigan (*a*) and Wisconsin (*b*) inland lakes (30 lakes sampled each year out of a population of 50 lakes, 10 fish sampled per lake).

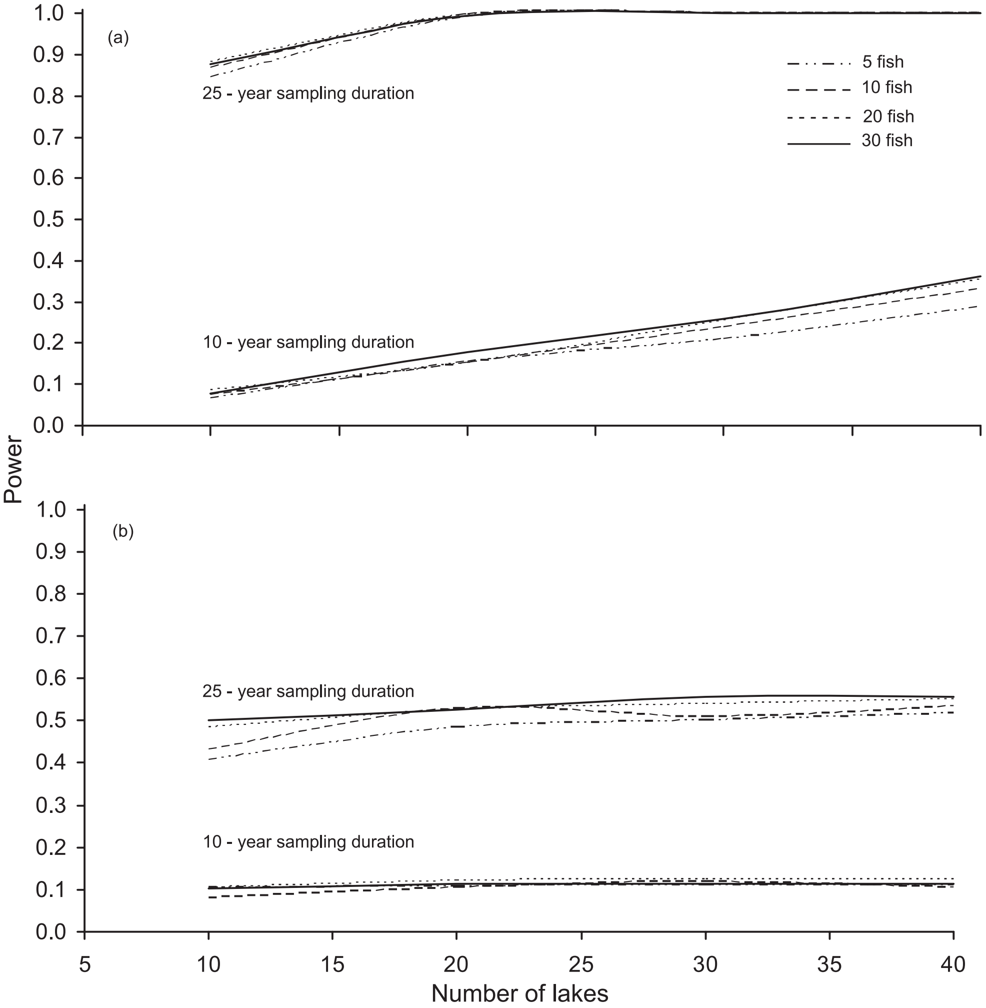


Discussion

Temporal trend

We detected four significant regional trends out of the 26 data sets analyzed, all of which were from inland lakes sampled in Wisconsin. Of these, one was positive (age 4 largemouth bass) and three were negative (ages 2, 3, and 4 walleye). The magnitude of the trends ranged from 0.5 to 0.9 mm·year^{-1}. No significant regional trends in mean length at age were detected from Michigan inland lakes. Although we detected four significant regional trends, any inference regarding causation is difficult (Stow et al. 1998); however, potential mechanisms can be hypothesized. For instance, potential causal factors of increasing trends in mean length at age include effective regional harvest regulations or increases in regional temperatures resulting in increased growth rates. However, if increases in regional temperature were responsible for the observed increasing trend, then we would expect that more of our data sets would demonstrate such a trend. Thus, temperature alone is likely not responsi-

Fig. 3. Power curves for detecting temporal trends in mean length at age for age 4 walleye (*Sander vitreus*) in Michigan (*a*) and Wisconsin (*b*) inland lakes as a function of the number of lakes sampled each year out of a population of 50 lakes and the number of fish sampled from each lake ($\lambda = -1.0$ mm·year^{-1}) for a 10- (bottom set of curves) and 25- (top set of curves) year sampling duration.



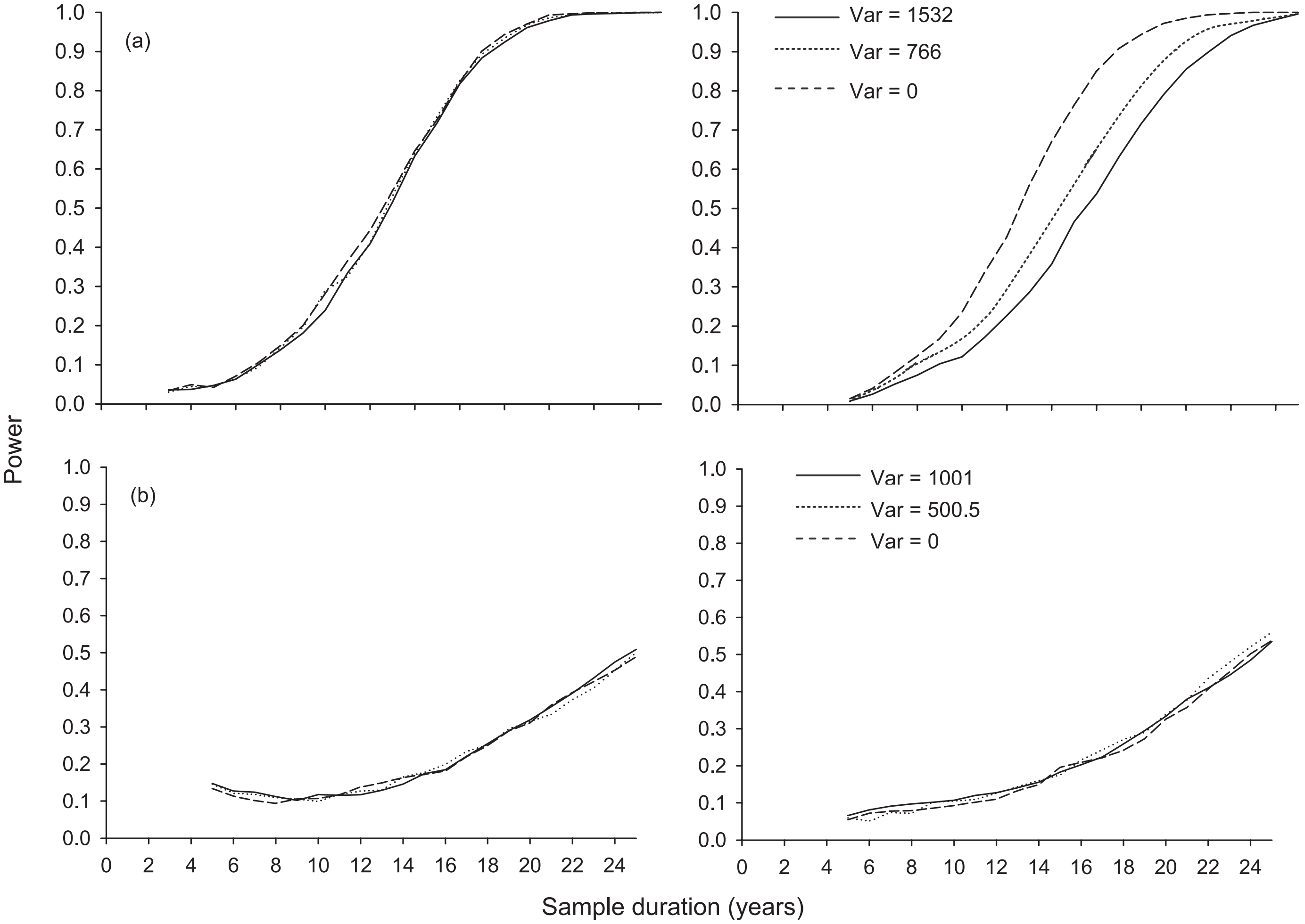
ble for the observed trend. Decreases in mean length at age for walleye could be due to effects of anglers or stocking programs. For example, if stocking rates increased over time or if fish numbers increased for some other reason, then increasing competition for resources could lead to reduced growth rates. This mechanism was also proposed by Li et al. (1996) to explain reduced mean weights of walleye in stocked lakes in Minnesota. However, the observed trends could be due to interactions of changing biotic and abiotic conditions over time, which make it difficult to attribute causality to any single source.

Variance components

The proportion of total variance attributed to each component varied considerably among the six data sets we examined. Across all six data sets, residual variation (variation due to sampling error) composed the largest percentage ($\bar{x}$ = 54%) of the total variance, while lake-to-lake and ephemeral temporal averaged 25% and 17% of the total variation, respectively. In contrast, coherent temporal variation and trend variation averaged only 3% and 0.1%, respectively. Furthermore, coherent temporal variation was only significantly different from zero in three out of six analyses, while trend variation was only significant in two analyses (likelihood ratio test, $P < 0.05$). However, our variance estimates are within the percentages reported by Osenberg et al. (1988). Osenberg et al. (1988) partitioned variance in annual increment in length of bluegill and pumpkinseed into four components: residual error, lake, year, and lake × year. On average, residual error variance composed 69% of the total variance, whereas, lake-to-lake variability and lake × year variation composed an average of 20% of the total variance. They found that year effects (coherent variation) did not explain any of the variance. For our analyses, the relatively high residual variation is likely due to measurement error (e.g., errors made during the reading of scales for age determination), variation among individual fish, errors in data processing, crew effects, and collection protocol sampling errors that may have occurred over the time period we examined.

Examining variance structures of monitoring indices has been performed for several lake indicators, primarily using data obtained from the United States Environmental Protection Agency's Environmental Monitoring and Assessment Program (EMAP) in the northeastern USA. The EMAP collected data on a wide range of chemical and biological data,

Fig. 4. Power curves for detecting temporal trends in mean length at age for age 4 walleye (*Sander vitreus*) in Michigan (*a*) and Wisconsin (*b*) inland lakes. Lake-to-lake variance is shown at the estimated value from historical data (solid line), decreased by 50% (dotted line), and set to zero (longer dashed line) ($\lambda = -1.0$ mm·year^{-1}, 30 lakes sampled each year, 10 fish sampled per lake). Power curves represent a scenario when 60% of the population of lakes is sampled each year (population of 50 lakes, left panels) or a scenario when 3% of the population of lakes is sampled each year (population of 1000 lakes, right panels).



including water chemistry measures of conservative and nonconservative ions and biological measures such as fish and zooplankton species richness (Stemberger et al. 2001; Kincaid et al. 2004). The variance structures in our analysis of fish mean length at age were within the ranges for zooplankton abundance indicators from the EMAP described by Stemberger et al. (2001), although these authors did not estimate slope variation in their study. For zooplankton abundance indicators, percent lake-to-lake variation ranged from 0% to 69%, coherent temporal variation was “small or negligible”, ephemeral temporal variation ranged from 0% to 16%, and residual variation ranged from 14% to 43% (Stemberger et al. 2001).

For some biological indicators, such as fish mean length at age in our study and zooplankton abundances and species richness estimated for the EMAP data, the proportion of residual variance is much higher compared with conservative chemical indicators, such as calcium and magnesium (Kincaid et al. 2004). For conservative chemical indicators, lake-to-lake variation composes a majority of the total variation, and there is relatively low residual variance (Kincaid et al. 2004). The high spatial variation among lakes and low residual variation for conservative ions likely reflects the relative stability of these indicators within lakes over time and space compared with nutrients and biological measurements that are controlled more by within-lake processes and which are more prone to sampling error (e.g., have higher within-lake spatial and temporal variation). These differences between conservative chemical indicators and biological indicators need to be acknowledged and incorporated into the expectations of monitoring programs. For example, detecting a prespecified trend for a biological indicator with a large residual variance component will require a longer sampling period compared with indicators with lower residual variances to detect the same trend, all else being equal. While it might be possible to reduce sampling errors associated with biological indicators, this often may not be the best choice unless little cost is involved (see Power analysis below).

Power analysis

We observed the expected increase in power with increasing trend magnitude and number of years sampled for both the Michigan and Wisconsin analyses. This pattern was also

Table 4. Mean percent increase in statistical power due to setting the estimated residual and coherent yearly variance to 50% and 25% of estimated values.

	Residual variance		Coherent temporal variance		Coherent temporal and residual variance
	50%	25%	50%	25%	25%
Mean percent increase	3	5	35	95	103

Note: The power estimates correspond to a temporal trend of –1.0 mm·year^{-1} in mean length at age for age 4 walleye (*Sander vitreus*) sampled in Wisconsin inland lakes. The mean percent increase reported is the average percent increase in power over the sampling period (5–25 years) compared with a situation using the estimated variance components from historical data (see Table 3 for variance estimates; population of lakes = 50, 30 lakes sampled each year for 25 years, 10 fish sampled per lake).

demonstrated using the EMAP data (Urquhart et al. 1998). A striking difference between the Michigan and Wisconsin power analyses, however, was the overall low power observed for the Wisconsin data. We expected power to be lower for the Wisconsin analyses because of the higher proportional and absolute value of the estimated coherent temporal and residual variation compared with the Michigan analyses (see below), but we were not certain as to the relative affects of each component (coherent temporal or residual) on power. Furthermore, because Urquhart et al. (1998) demonstrated the importance of coherent temporal variance in reducing trend detection, we wanted to examine its relative effect compared with the much greater proportion of variance attributed to sampling error. To examine this in more detail, we performed a sensitivity analysis using the Wisconsin data. Again, because the Wisconsin variance components that differed most from the Michigan data set were the residual variance (composing 76% of the total variation for Wisconsin ($\hat{\sigma}_e^2 = 4936$) versus 18% for Michigan ($\hat{\sigma}_e^2 = 550$) and coherent temporal variance (composing 4% of the total variation for Wisconsin ($\hat{\sigma}_b^2 = 261$) versus nonsignificant for Michigan), we concentrated our sensitivity analysis on these two components. We set both the residual and coherent temporal variance to 50% and 25% of the estimated values while holding all other variance components at their estimated values. We then reduced them simultaneously while holding all other variances at their estimated values and calculated the mean percent increase in power compared with the baseline situation when only estimated values were used. We report the mean percent power increase representing the average percent increase in power over the sampling period (5–25 years) compared with a situation using the estimated variance components. The mean percent change was calculated as

$$(2)\qquad \left\{\sum_{i=5}^{25}[(\text{power\_reduced}_i - \text{power\_full}_i)/(\text{power\_full}_i)]\times 100\right\}/21$$

Where power_reduced$_i$ is the power to detect a –1.0 mm·year^{-1} trend under the scenario of reduced residual or coherent temporal variation in year i, and power_full$_i$ is the power to detect the same trend under the scenario using the estimated variance components from eq. 1 in year i.

The sensitivity analysis revealed that the coherent temporal variation had a large effect on the power to detect trends (Table 4). Reducing the coherent temporal variation to 50% and 25% of the estimated value led to an average percent increase in power of 35% and 95%, respectively. Conversely, setting the residual variance to 50% and 25% of estimated values led to only 3% and 5% increases in power, respectively. Thus, even though coherent temporal variation composed only 4% of the total variation for Wisconsin and residual variation composed 75% of Wisconsin's total variation, coherent temporal variation had a disproportionately large influence on the power to detect trends. However, once the coherent temporal variance was set to 25% of the estimated value, setting the residual variance to 25% of the estimated value did lead to a slightly larger increase in power, a further 8% increase over the baseline estimates when compared with just setting coherent temporal variance to 25% of estimated value. Although it is unknown why coherent temporal variance was large for the Wisconsin analysis, possible sources of this coherent variation include factors that impact fish populations at a regional scale, such as annual differences in temperature.

We further investigated the relatively large coherent temporal variation for the Wisconsin data by examining the magnitude of best linear unbiased predictors for year effects. Our examination showed that the relatively high variance for the Wisconsin data set was not due to one or a few years, but rather a generally broader distribution of year effects. We examined data for years in the Wisconsin data set that had large effects (i.e., those years with greater than 1 standard deviation from the mean) to see if they differed from other years in the number of lakes sampled. Years that had large effects were often years when very few lakes were sampled or for years where a number of the sampled lakes were not sampled in any other year (i.e., few revisited sites). However, it is difficult to generalize as to why some years showed a large effect while others did not, because there were also years with small effects that were characterized by these same sample characteristics, including some years in the Michigan data set, where coherent variation was much less.

The strong effect of temporal coherent variation to reduce trend detection capabilities was also demonstrated by Urquhart et al. (1998). Because this source of temporal variation cannot be reduced by changing the design of a monitoring program, only an increased sampling duration will lead to an increase in statistical power (Urquhart et al. 1998; Kincaid et al. 2004). This example illustrates the importance of examining variance components of potential monitoring indices, because even a small (as estimated as percentage of the total variation) coherent temporal variation component can reduce trend detection capabilities over the short term.

Although coherent temporal variation can greatly reduce power, the power to detect trends can also be affected by the allocation of resources to either sample more lakes per year or sample more fish per lake. The effect of increasing the number of lakes sampled each year versus increasing the number of fish sampled from each lake on the power to detect trends is important from a management perspective because this issue represents a resource allocation trade-off. Our analysis suggested that very modest samples within lakes will often be adequate and that often the focus should be placed on sampling more lakes rather than more or better at each lake. Others have previously argued that sampling more locations rather than more sampling at a location would often be a better approach for improving power (e.g., Larsen et al. 2004).

High lake-to-lake (spatial) variance has been shown to reduce the power to detect trends (e.g., Urquhart et al. 1998). In our analysis, the relative importance of lake-to-lake variance was dependent on the proportion of lakes sampled from the population of lakes each year. For example, in our power analysis based on the age 4 walleye Michigan data, we were able to obtain a better estimate of lake-to-lake variance when we sampled 60% of the lakes each year compared with sampling 3% of the lakes each year. Consequently a reduction in lake-to-lake variance did not have an appreciable effect on power under the 60% sampling scenario. However, when sampling only 3% of the population of lakes each year, lake-to-lake variation became more important, and reductions in this source of variation led to an increase in power. Thus, in situations with a large lake-to-lake variance component, it is advisable to consider designs that incorporate planned repeated sampling at some lakes so as to factor out some of the lake-to-lake variance and increase power, without having to sample a majority of the lakes in the region (see references for detailed discussion of sampling designs for trend detection and this issue). Furthermore, if repeated visits are not built into the design, sampling from a large population of lakes may limit what variance components are even estimable, as we saw for both actual and simulated data sets. Although it was not within the scope of this paper to explore the many alternative sampling designs, the type of sampling design employed, such as the use of fixed sites in combination with a random selection of lakes each year, can affect power to detect trends (Urquhart et al. 1998). With information on the components of variance for desired monitoring indices, management agencies can explore alternate designs in an effort to maximize power.

The use of historical data from state and federal agencies provides one source of data that can be used to investigate the presence of trends in fisheries data for multiple populations (e.g., this study; Reckahn 1986; Beard and Kampa 1999). Much of the historical data, however, were not collected following probability sampling methods, in which every sampling unit has a known probability of being sampled (Olsen et al. 1999). Rather, water bodies were often sampled based on expert choice (i.e., judgment sampling; Olsen et al. 1999), selected by convenience, or in response to local or regional political concerns (e.g., convenience sampling; Olsen et al. 1999). The nonprobability-based sampling associated with the historical data weakens the strength of the statistical inferences to the population of lakes or streams as a whole. Nevertheless, these data provide a unique opportunity to examine regional trends. Furthermore, because the implementation of probabilistic sampling designs is only now becoming more prevalent, historical data often represent the only source of information that can be used for the development of monitoring programs designed to describe the status of systems and to detect trends of aquatic indices.

Although the statistical power to detect trends is important to consider when developing a monitoring program, there are other components of a monitoring program that should also be considered. For example, the costs and benefits of implementing a monitoring design should be considered along with the uncertainties associated with alternative designs (MacGregor et al. 2002). Thus, power analysis represents one source of information to be used in the processes of designing an ecological monitoring program. Examining variance components of desired indices, power analysis, and other quantitative analyses that take into account uncertainties and expected benefits of monitoring programs represents powerful tools that will help fisheries management agencies develop effective monitoring programs.

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