Fisheries
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/ufsh20

Detecting Temporal Trends in Freshwater Fisheries Surveys: Statistical Power and the Important Linkages between Management Questions and Monitoring Objectives

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Published online: 11 Jul 2013.

To cite this article: Tyler Wagner , Brian J. Irwin , James R. Bence & Daniel B. Hayes (2013) Detecting Temporal Trends in Freshwater Fisheries Surveys: Statistical Power and the Important Linkages between Management Questions and Monitoring Objectives, Fisheries, 38:7, 309-319, DOI: 10.1080/03632415.2013.799466

To link to this article: http://dx.doi.org/10.1080/03632415.2013.799466

Detecting Temporal Trends in Freshwater Fisheries Surveys: Statistical Power and the Important Linkages between Management Questions and Monitoring Objectives

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ABSTRACT: *Monitoring to detect temporal trends in biological and habitat indices is a critical component of fisheries management. Thus, it is important that management objectives are linked to monitoring objectives. This linkage requires a definition of what constitutes a management-relevant "temporal trend." It is also important to develop expectations for the amount of time required to detect a trend (i.e., statistical power) and for choosing an appropriate statistical model for analysis. We provide an overview of temporal trends commonly encountered in fisheries management, review published studies that evaluated statistical power of long-term trend detection, and illustrate dynamic linear models in a Bayesian context, as an additional analytical approach focused on shorter term change. We show that monitoring programs generally have low statistical power for detecting linear temporal trends and argue that often management should be focused on different definitions of trends, some of which can be better addressed by alternative analytical approaches.*

Detección de tendencias temporales en muestreo de pesquerías continentales: poder estadístico y las relaciones entre temas de manejo y objetivos de monitoreo

RESUMEN: *el monitoreo que se realiza para detectar tendencias en el tiempo de índices biológicos y de hábitat es un componente crítico para el manejo de pesquerías. Por tanto, es crucial que los objetivos de manejo estén concertados con los objetivos de monitoreo. Estas relaciones requieren de la definición de los constituyentes de una "tendencia temporal" que sea relevante para el manejo. También es importante desarrollar expectativas acerca de la cantidad de tiempo necesaria para detectar una tendencia (i.e. poder estadístico) y elegir un modelo estadístico apropiado para el análisis. En este trabajo (1) se presenta un panorama de las tendencias temporales que comúnmente se encuentran en el manejo de pesquerías, (2) se revisa la literatura publicada sobre evaluación del poder estadístico en la detección de tendencias temporales y (3) se aplicaron modelos lineales dinámicos de contexto Bayesiano, como un enfoque analítico adicional enfocado en cambios de corto plazo. Se muestra que los programas de monitoreo generalmente tienen bajo poder estadístico para detectar tendencias lineales en el tiempo y se argumenta que el manejo debiera enfocarse en diferentes definiciones de tendencias, algunas de las cuales pudieran ser mejor estudiadas mediante enfoques analíticos alternativos.*

INTRODUCTION

Fisheries management agencies use a variety of methods to survey fish populations and their habitats. These surveys provide a wealth of information, including indices of relative abundance, descriptions of the size and age composition of the population, and assessment of habitat conditions (Murphy and Willis 1996; Roper et al. 2002). Although data obtained from these surveys are used to assess a variety of management and conservation objectives, a common theme is to monitor trends in biological or habitat indices over time (for conciseness, we use the term "trend" to include linear and nonlinear changes over time, including abrupt step changes). Detecting temporal trends has many implications in fisheries management. Some reasons why trend detection is important include (1) management actions often have time-oriented objectives (e.g., use stocking to restore fish populations within 10 years or stabilize eroding stream banks to immediately reduce sedimentation rates); (2) aquatic ecosystems may respond in complex and nonlinear ways to both natural and anthropogenic factors, resulting in unanticipated changes (Hayes et al. 2003a; Irwin et al. 2009; Rudstam et al. 2011); and (3) knowledge of previous system dynamics can inform structured decision-making processes by helping to identify what can realistically be considered acceptable or unacceptable outcomes of management (Irwin et al. 2011).

Although the concept of trend detection is not unique to fisheries assessment, the critical role that monitoring plays in fisheries management decision making emphasizes the importance of linking value-based management objectives to statistically based monitoring objectives. Establishing this linkage requires a definition of what constitutes a management-relevant trend. It is also important to develop expectations for the amount of time required to detect a management-relevant trend in a system indicator, with some level of confidence (i.e., statistical power), as well as choose an appropriate statistical model for analyzing survey data. Knowing the amount of time required to detect a temporal trend allows managers to identify cases where the time frame for management (e.g., stocking decisions that are made annually or every few years) differs from the time frame necessary to detect responses in the state of a system. Even when managers have access to long-term monitoring data, the reality is that many fishery management decisions are made in a "low statistical power environment" (see section Summary of Published Power Analyses). The negative consequences of this unfortunate reality may be at least partially alleviated by deliberate coordination of monitoring and management efforts. When properly designed, monitoring programs can provide a critical feedback loop for learning about system dynamics, which is fundamental to adaptive management (Lyons et al. 2008; Lindenmayer and Likens 2010). Thus, managers should be able to make more informed decisions when monitoring programs are designed to reduce key uncertainties. In turn, monitoring programs can also be used to evaluate how well observed outcomes correspond with anticipated responses to a management action.

In this article, we connect common fishery management questions to examples of monitoring objectives of detecting temporal trends. We discuss how different trend detection monitoring objectives can be translated into different statistical models and why this translation is critical for evaluating value-based management objectives. Within this context, we characterize several common issues that influence the statistical power of trend detection, and we discuss some advantages of Bayesian inference as an alternative to null hypothesis testing for making inferences about temporal trends. There are four major components to this article: (1) a brief overview of different types of temporal trends encountered in fisheries management, (2) a review of previously published studies that evaluated statistical power of long-term trend detection, (3) presentation of newly generated power analyses for detecting long-term trends using data from several fishery-independent surveys in the Great Lakes basin, and (4) an illustration of an additional, flexible analytical approach (i.e., dynamic linear modeling) geared toward alternative definitions of temporal trends. Our intent is that our literature review, illustrative examples, and discussion will better position resource managers to establish and communicate realistic expectations for temporal trend detection in freshwater fishery surveys.

Temporal Trend Detection in Fisheries Monitoring

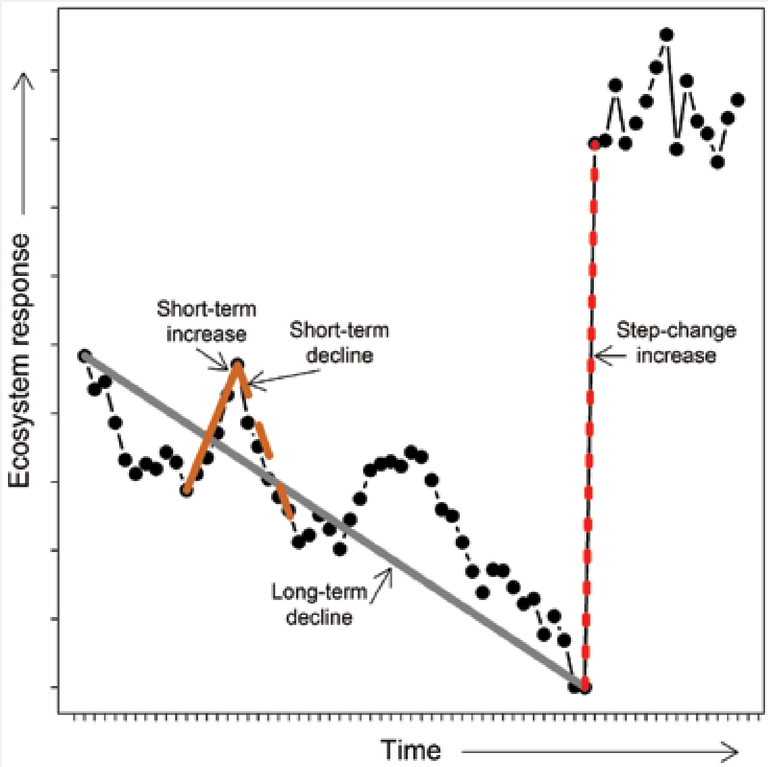
The degrees to which time-oriented *management objectives* are met are often assessed by (sometimes implicit) *monitoring objectives* that require detecting temporal trends. Simply put, fishery managers are often interested in whether important metrics have changed over time, particularly in response to management interventions (e.g., changes in fishing regulations). For example, consider a management action that has an objective of increasing the abundance of legal-size sport fish and a fishery-independent survey expected to assess the degree to which this management objective is being reached. In this case, a fishery manager may wish to "… detect an increase in the catch per effort (CPE) of legal-size fish within 5 years." When monitoring objectives are stated this way, they are often interpreted analytically as "… detect a statistically significant linear trend in in the logarithm of CPE of legal size fish within 5 years." Typically when assessing trends, a constant percentage change is estimated and hence an exponential trend is estimated using logarithms. Thus, to evaluate the management action, survey data are often examined for a statistically significant linear increase or decrease over time (Urquhart et al. 1998; Larsen et al. 2001), although the relative familiarity with statistical approaches that assume linearity may be partly responsible for the commonality of these types of analyses. Linear trend detection may often be sufficiently informative, even for nonlinear time series, as a long as a monotonic increase or decrease is present in the data (Urquhart and Kincaid 1999). However, this definition of temporal trend does not capture all of the important nuances of how aquatic systems can undergo temporal change, particularly when management actions are being frequently adjusted.

In addition to detecting short- or long-term trends persistent in monitoring data, fisheries managers are often interested in abrupt shifts to system conditions. Thus, detecting a long-term linear trend may not adequately represent monitoring objectives associated with large-scale management actions or system disturbance (e.g., establishment of invasive species). In this case, alternative statistical models must then be used to adequately address monitoring objectives. For instance, there are a variety of analytical approaches that can be used to detect thresholds in aquatic systems (e.g., Brenden et al. 2008; Baker and King 2010) that occur when the response of a system changes abruptly at some threshold value. For instance, Thomson et al. (2010) used a Bayesian change point analysis to identify periods of step changes in absolute abundance and in trends of change in abundance of four pelagic fish species in the upper San Francisco Estuary, California. In their case, identifying whether, and when, abrupt changes occurred helped to elucidate underlying causes and could help identify potential mitigation measures (Thomson et al. 2010): causes and management options that may not have been identified if statistical methods were used that only focused on detecting linear trends. Likewise, the detection and assessment of regime shifts in aquatic systems has been receiving increasing attention (Carpenter 2003; Carpenter et al. 2011). Thus, monitoring programs are often expected to provide answers to management questions about changes occurring over time, and frequently there can be multiple definitions (or interpretations) as to what these questions mean in terms of detecting temporal trends (Panel 1).

Statistical Power to Detect Long-Term Linear Trends

As reviewed above, detecting a temporal trend is often equated with finding a statistically significant long-term linear trend. This definition of temporal trend relies on linear models and null hypothesis testing as a means of making inferences about temporal dynamics, and thus the concept of statistical

PANEL 1. INTERPRETING TEMPORAL TRENDS.



Fisheries management objectives often specify a desire to detect temporal trends in an ecosystem response variable of interest. As a result, monitoring is included as part of the management process in an effort to evaluate whether or not a temporal trend has occurred. In this situation, translating management questions to monitoring objectives becomes a critical part of the overall management process. A key component to this translation is defining what is meant by "temporal trend." including both the duration of change sought to detect (a short- vs. long-term trend) and the anticipated form of the trend (e.g., linear, nonlinear, step change). The figure shows hypothetical nonmonotonic temporal dynamics of a fishery ecosystem response variable (solid black circles). The time series includes a long-term trend (grey line) describing an underlying long-term average decline over most of the time period. Within this period of long-term decline are shorter term trends, both increases and more severe declines compared to the long-term average (e.g., solid and dashed orange lines), illustrating that short-term trends may or may not be representative of long-term dynamics. The dashed red line indicates an abrupt step change (i.e., a threshold or "tipping point") in the time series. To translate management questions to monitoring objectives, we suggest that managers specify the anticipated rate, duration, and form of temporal trend to be detected. We have provided some illustrative examples in Table P1.

Table P1. Examples of common management questions related to temporal trends encountered in fisheries and descriptive characteristics related to translating these questions to monitoring objectives.

Example management question	Rate of temporal change	Duration of temporal change	Form of temporal trend	Example monitoring objective
Is the target population long-term average declining over time?	Usually gradual, sustained	Long-term cycles or permanent	Linear: Long-term trend[a]	Detect an underlying trend in the population over time
Is a strong year-class present?	Usually moderate	Short-term	Nonlinear: Short-term trend[a]	Detect a large recruitment event
How different are two time periods from one another (e.g., before and after a management action was implemented)	Rapid	Permanent over moderate to long-term time scales	Step change: Potentially a regime shift; steady-state conditions of meaningful duration	Detect a shift in system productivity
Has the target population increased each of the last 5 years	Moderate	Short-term to permanent	Linear: Short-term trend	Detect an increase/decrease in abundance due to a management action

[a]In practice, linear trends are often estimated on the natural logarithm scale.

power is used for evaluating trend detection capabilities. This approach also implies that whether or not a long-term (e.g., decades) linear trend is detected provides meaningful information on whether a system is responding to a management action as predicted. However, monitoring data may also be used to evaluate management actions over relatively short ecological time frames (e.g., 5–10 years). In this case, managers may not be interested in the long-term dynamics of a population but, rather, in whether conditions have changed from year to year or perhaps in the last 5 years. If traditional linear models are used to make inferences about the success of management actions under these circumstances, managers may be setting themselves up for failure because of the low statistical power to detect linear trends over relatively short, management-relevant time frames (<10 years). Failure can come in the form of not detecting a significant trend even though some biologically important change has occurred (although perhaps less likely in fisheries, failure could also come in the form of detecting a significant trend, due to relatively low total variability, that is not meaningful from a biological or management perspective; Wade 2000). To illustrate this point, we conducted a literature review on the power to detect statistically significant linear trends for freshwater biological and habitat indices.

Statistical power is the probability of rejecting the null hypothesis when it is, in fact, false (e.g., detecting a trend when a trend is present). Generally, power is a function of sample size, the choice of a type I error rate (usually represented as α; i.e., stating that a trend is present when, in fact, there is not a trend), effect size (i.e., trend magnitude), the underlying variance in the observations, and the statistical model used to evaluate power. When survey data are analyzed for temporal trends, sample size is often quantified as the number of years sampled and the number of sampling units sampled within a year. Common examples of fishery-related sampling units include the number of reaches surveyed within a stream, the number of sites visited within a lake, or the number of lakes sampled. In many power analyses, the significance level (α) is set at a conventional value of 0.05, but larger values are sometimes chosen if failing to detect a real trend in an index is deemed more important than detecting a false trend (e.g., Dauwalter et al. 2010). The magnitude of the effect size is generally stated as the desired amount of change over time that a management body is interested in detecting. Therefore, the desired detectable trend magnitude is often stated as a percentage change per year (e.g., detect a 3% per year decline in fish abundance) for power analyses evaluating the statistical power of detecting long-term linear trends. There are several sources of variability that affect statistical power to detect trends in fishery survey data (e.g., spatial, temporal, sampling [observation] error; Urquhart et al. 1998; Larsen et al. 2001), and previous work has also shown that how the total variability is partitioned among different sources is an important determinant of the statistical power associated with temporal trend detection (Wagner et al. 2007).

Summary of Published Power Analyses

Using previously published power analyses, we summarized the number of sampling years required to detect statistically significant linear trends, and we used statistical power as a means to compare across studies and biological and habitat indices. This review highlights the low statistical power of many fishery surveys that are evaluated in this manner as well as the nontrivial nature of explicitly defining temporal trend when developing management/monitoring objectives and, importantly, when deciding on the analytical method used for estimating temporal trend-related parameters.

We focused our literature review on recently published studies (from 1999 to 2011) that examined the statistical power to detect temporal trends in biological and aquatic habitat survey data. Specifically, we summarized the number of years needed to detect a trend of a given magnitude with a power ≥ 0.80. For fisheries survey data, power ≥ 0.80 is typically deemed as acceptable or "high" power. From the papers we reviewed, we report the stated temporal duration required for trend detection or we estimated the number of years from presented power curves when the number of years required to detect a trend was not directly indicated in the text. Although there are several factors that affect statistical power, we summarized the number of years required to detect a trend with respect to both the type I error rate and trend magnitude. We focused on these two influential factors because (1) they represent critical aspects of developing objectives for monitoring programs and (2) relative to other factors, such as within-year sample size, they have a large influence on power estimates. Although within-year sample size can influence statistical power for an individual study, we did not summarize the published power analyses based on sample size because for a given trend magnitude and sample duration, the range of sample sizes evaluated in the published literature did not often result in large changes in power. For example, the number of years required to detect a 1% per year trend in canopy cover with 80% likelihood ranged from 15 years when 10 sites were sampled each year to 13 years when 50 sites were sampled each year (Larsen et al. 2004). This small to moderate gain in power as a result of increasing within-year sample size is not unexpected because increasing sample size will not reduce all sources of variation affecting observations of fish populations and their habitat. Specifically, if coherent temporal variation is high (i.e., a strong year effect), neither increasing within-year sample size or within-year revisits to the same sites will have much influence on power (Urquhart et al. 1998; Larsen et al. 2001). Thus, plots of statistical power often display an asymptotic relationship with sample size in ecological studies. If a study did report the number of years to detect a trend for multiple sample sizes, however, we recorded and report all power estimates in an effort to capture some of the variability in power that is due to sample size. For studies that evaluated different sample designs (i.e., fixed site versus revisit monitoring designs), we report the average power across designs. This approach was used because survey sampling design tended to have a minimal impact on power estimates (e.g., Dauwalter et al. 2010) and relatively few designs were evaluated in most

Table 1. Summary of studies examining the statistical power to detect temporal trends in freshwater fishery survey data.

Indicator	System type	Design evaluated[a]/ scope of inference	Trend magnitude (percentage per year)[b]	Sampling duration (years)	Number of sites sampled per year[c]	α-Level	Reference
Biological							
Abundance and biomass for stream trout (*Salmo, Salvelinus*, and *Oncorhynchus* spp.[d])	Streams	Rotating panel/single site and network of sites	−2.5, −5	5–30	1–30	0.05, 0.10, 0.20	Dauwalter et al. (2009)
Trout biomass (Brook Trout *S. fontinalis*, Rainbow Trout *O. mykiss*, and Brown Trout *S. trutta*)	Streams	Rotating panel/ National Forest	−1, −2.5, −5	6–30	20–30	0.05, 0.10, 0.20	Dauwalter et al. (2010)
Bull Trout *S. confluentus* indices of abundance and population estimates	Streams	Fixed sites/ watershed	−25, −50, −75[e]	5, 15, 30	10–39	0.10	Al-Chokhachy et al. (2009)
Coho *O. kisutch* and Steelhead *O. mykiss* redd densities	Streams	Generalized random tessellation stratified design and stratified random design/regional	±5, ±10	3–18	8–40	0.05, 0.10	Gallagher et al. (2010)
Bull Trout *S. confluentus* redd counts	Streams	ND/state	0, ±10, ±20, ±50	3–30	1	0.05, 0.20	Maxell (1999)
Walleye *Sander vitreus* mean length at age	Inland lakes	Fixed sites/ regional	−0.5, −1.0, −1.5, −2.0	5–25	10–40	0.05	Wagner et al. (2007)
Walleye S. vitreus catch per effort	Great Lakes	Fixed sites/ single lake	−3, −5, −10, −20	5–25	10–100	0.05	Wagner et al. (2009)
Habitat							
Large wood volume (m^3/100 m)[f]	Streams	Rotating panel/coastal streams	1, 2	5, 10, 15	48	0.10	Anlauf et al. (2011)
Residual depth, riparian canopy cover, percentage of fine substrate (<2 mm in diameter), volume of large wood per unit length of channel	Streams	Fixed sites/ regional	1, 2	3–30	10–50	0.05	Larsen et al. (2004)

[a]For conciseness, we used "rotating panel" to include several types of revisit panel designs (see Urquhart and Kincaid 1999 for design details). ND = no design specified.
[b]Negative values indicate declines; positive values indicate increases over time; ± indicates that both increases and decreases for a given trend magnitude were evaluated.
[c]The definition of a "site" varies by study; see reference for details.
[d]Examined data from eight studies representing 22 streams.
[e]Statistical power was performed to detect a specified decline (e.g., 25, 50, or 75%) over a given time period, not on a per year basis.
[f]Variance structures for active channel width (in meters), percentage fine sediment, and percentage pool habitat were similar to large wood volume and assumed to have similar power.

published studies. For studies that reported power analyses based on actual variance estimates and alternative hypothetical variance structures (e.g., Wagner et al. 2007), we report power based on the actual variance estimates. Because we were interested in routine monitoring programs, we did not consider studies that examined the power to detect trends as a result of using management experiments (e.g., before–after–control–impact designs), although we comment on such management experiments in our discussion.

We found seven studies evaluating multiple biological indices (41 power analyses) and two studies evaluating habitat indices (43 power analyses) that met our criteria and were included in our summary of power. Biological indices included measures of fish abundance, biomass, density, CPE, redd counts, and mean length at age. In these studies, the biological indices were usually related to salmonids (*Salmo*, *Salvelinus*, and *Oncorhynchus* spp.), with the exception of two studies (Wagner et al. 2007, 2009) with Walleye *Sander vitreus* as the focal species. Habitat indices included measures of large wood volume, residual depth, riparian canopy cover, and percentage of fine substrate (Table 1). Not unexpectedly, on average, the number of years required to detect a trend decreased with increasing trend magnitude and the chosen significance level. Though there was moderate variation in the number of years required to detect a trend for the same significance level and trend magnitude (Figure 1), some generalizations emerged. The number of years required to detect trend magnitudes less than a 5% change per year (e.g., 0.5, 1, 1.5, or 2%) was ≥ 10 years (mean ± standard deviation [SD], 19 ± 5, $n = 15$) for biological indices. The number of years to detect a trend was < 10 years only when relatively large trend magnitudes were specified (e.g., a 10% or 20% change per year) or when moderate trend magnitudes (e.g., 5% change per year) and a type I error rate of 0.10 or 0.20 were adopted (see Figure 1). Although a smaller range of trend magnitudes was evaluated for habitat indices, similar patterns emerged. For instance, for a 2% per year change, the average number of years to detect a trend was 13 ± 4 (±SD, n = 22). Similar to biological indices, at the smallest trend magnitude evaluated (e.g., 1% change per year), it always required > 10 years to detect a trend (mean ± SD, 21 ± 6, n = 21; see Figure 1).

Great Lakes Basin Power Analysis Examples

To supplement the literature review, we performed power analyses based upon Walleye and Yellow Perch *Perca flavescens* fishery-independent gillnet surveys in three lakes in the Great Lakes basin. Specifically, we analyzed surveys from the Wisconsin waters of Lake Superior (Walleye and Yellow Perch); the Bay of Quinte, Lake Ontario (Walleye and Yellow Perch); and Oneida Lake, New York (Walleye only) to estimate variance structures. Catch per effort data were from fixed site gillnet surveys, where gillnets were fished at multiple sites within each lake each year, and the same sites were revisited each year. We then used a simulation approach for power analysis following the methods outlined in Wagner et al. (2007). Briefly, for each simulation for each lake, we used variance components estimated for each observed time series to simulate a hypothetical 30-year time series of catch data for 1,000 sites. These 1,000 sites were then treated as the total population of sites from which samples could be taken for that lake. A known population-average temporal trend (a 2% per year decline) was then imposed on each site-specific time series. However, each simulated site could deviate from this population-average trend; the magnitude of the deviation was dependent on the estimate of trend variation used in the simulation. We ran 250 simulations based on the survey estimates for each lake. For all data sets, at the start of each simulation 30 sites were randomly chosen and then treated as the fixed sites that were sampled throughout a 30-year sampling period. Although we observed minimal effect of within-year sample size on power through our literature review, we also performed simulations where 60 sites were sampled each year to further evaluate the influence of within-year sample size on power. These supporting sensitivity analyses using 60 sites were performed for Lake Superior Walleye and Lake Ontario Walleye and Yellow Perch. During 3-year intervals of each simulation (i.e., at years 3, 6, 9, etc.), we used a negative binomial mixed model to estimate the fixed slope parameter and test the null hypothesis that it was equal to zero by calculating a test statistic and comparing to a critical value (α = 0.05). Because the data were generated assuming a negative slope, the null hypothesis of a zero slope is false, and power was estimated as the percentage of simulations (out of 250) that rejected the null hypothesis.

These analyses demonstrated similar statistical power patterns to those reported in the literature we reviewed. We present detailed results for the 30 site simulations only, given that the number of sites sampled had a modest influence on the results, which supports findings in the literature review. For example, for Lake Superior Walleye, going from 30 to 60 sites resulted in an average percentage increase of power over the 30-year time period of 0.28%, and for Lake Ontario Walleye and Yellow Perch the average percentage increase in power was 6.4% and 1.3%, respectively. For the 30-site case approximately 15 years of sampling was required to detect a 2% per year decline in Walleye CPE (power ≥ 0.8) in Oneida Lake and Lake Superior, whereas >30 years of sampling was required to detect the same trend for Lake Ontario Walleye (Figure 2). The results were similar for Yellow Perch, with approximately 15 and 22 years of sampling required to detect a 2% decline per year in lakes Ontario and Superior, respectively (Figure 2). The aforementioned percentage increases in power as a result of sampling 60 sites per year had minimal to no influence on the number of years required to detect a 2% trend with power > 0.8 when compared to sampling 30 sites per year. Another way of saying this is that power approaches an asymptote well within the range of sample sizes typically considered in fisheries studies, and thus power for trend detection is dominated by the influence of among-year variation and number of years sampled, rather than only among-site variation and the number of sites samples.

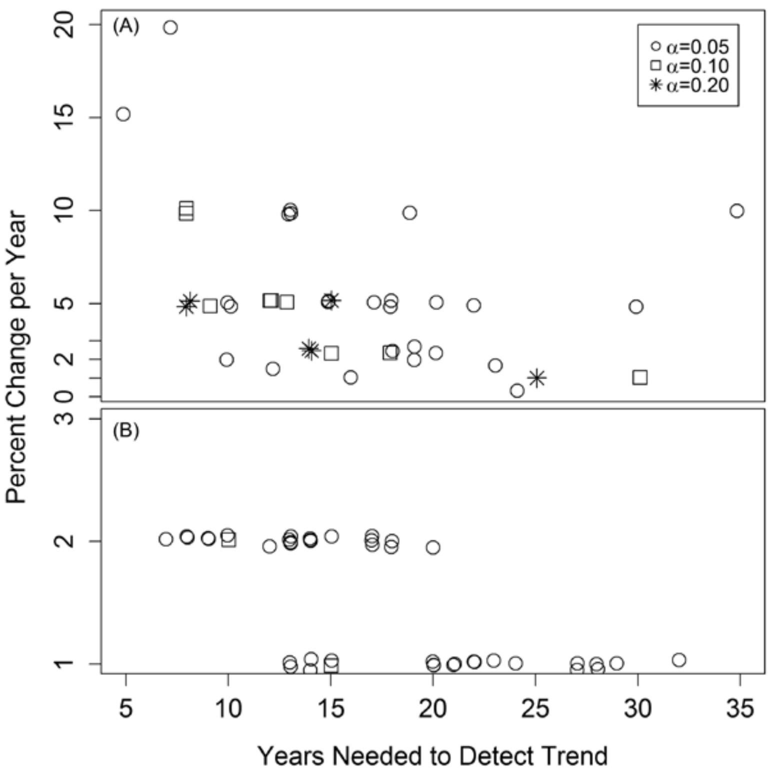


Figure 1. Summary of literature describing the years needed to detect a trend of a given magnitude with statistical power ≥ 0.80 for (A) biological and (B) habitat survey indices. Results are summarized by the significance level (α). Points have been jittered along the x- and y-axes to aid visualization. See Table 1 for studies used in the summary.

Dynamic Linear Modeling of Time Series Using Bayesian Estimation Techniques

Familiarity with standard linear regression techniques probably leads to their use even when management interest is not really in detecting a long-term overall trend across a time series. Rather, management interest often may center on what the rate of change is over a shorter term and how changes in this rate might coincide with management actions or other events. Estimates of the probability that the rate of change is less than some specified value (e.g., zero) can often be more useful than estimates of the probability that observed data arose in the absence of an underlying trend (the *P*-value from a hypothesis test). Given this, dynamic linear modeling in a Bayesian context is one tool that might better fit some management objectives. Dynamic linear models provide greater flexibility than linear regression by allowing the rate of change to also change over time. The use of Bayesian inference has grown in usage over time (e.g., Ellison 2004; Fabricius and De'ath 2004); however, it remains less commonly used than frequentist approaches for evaluating trends. One of the major advantages of Bayesian inference is that it emphasizes the relative probability of given rates of change, allowing for a more complete picture of the plausibility of different system dynamics.

Bayesian estimation can provide a flexible analytical framework for quantifying temporal trends, which also allows for probabilistic statements about outcomes that can facilitate communication of uncertainty to stakeholders. For instance, Bayesian analyses provide a probabilistic uncertainty estimate for all estimated parameters and derived quantities. Rather than relying on null hypothesis testing and with the resulting binary decision of a statistically significant or nonsignificant trend, Bayesian estimation allows for multiple decision possibilities and a more intuitive interpretation about the probability of a decline occurring in the time series (Wade 2000). As a result, trends can be evaluated and decisions made based on policy-relevant criteria that have been identified for any specific problem under consideration. In addition, although beyond the scope of this article, power analyses can be performed within a Bayesian context, providing estimates of the probability of achieving specific goals (rather than rejecting the null when the null is false) under different monitoring scenarios. Lastly, Bayesian analyses can take advantage of information that existed prior to a study to help inform inferences from the study (i.e., the use informative priors), whereas frequentist approaches assume that there is no relevant existing information (Ellison 2004). This may be useful in cases where information is available for the potential value of a parameter of interest.

To illustrate the concept of matching statistical models with monitoring objectives and the use of Bayesian inference, we further investigate the potential impacts of the establishment of an invasive species on Walleye in Oneida Lake, New York. Like many aquatic systems, Oneida Lake has been affected by many natural and anthropogenic stressors, including invasive species. Of notable importance was the invasion of zebra mussels *Dreissena polymorpha*, which were found in high abundance in the lake by 1992. Although the effects of zebra mussel establishment can cascade through trophic levels and vary among species and across life stages, for Walleye it was hypothesized that the establishment of zebra mussels would have a net negative impact, such that Walleye abundance was expected to decline (Irwin et al. in press). Specifically, it was predicted that declines in Walleye CPE would be evident post–zebra mussel invasion (i.e., post-1992), although double-crested cormorants also likely influenced Walleye abundance during this time period (Rudstam et al. 2004; Irwin et al. 2008).

For illustrative purposes, suppose that a monitoring objective related to Oneida Lake Walleye involved detecting temporal trends in CPE after zebra mussel invasion. The prediction that declines in Walleye CPE would occur after zebra mussels were abundant does not translate naturally to detecting a long-term linear decrease in Walleye CPE or its log. For this hypothetical monitoring objective, we are not interested in the long-term average trends in CPE; rather, we are interested in a potentially abrupt change in CPE connected to when zebra mussels became established. Specifically, we predict nonmonotonic trends in Walleye CPE over time, with a substantial decline occurring over a relatively short period after 1992, when zebra mussels were first observed at high densities in the lake. Further, it is likely that Walleye CPE would eventually level off at some lower but positive abundance (i.e., zebra mussels alone were not expected to drive any fish species to extinction).

To translate our prediction and monitoring objective for detecting nonmonotonic trends into a Bayesian statistical model, we fitted a dynamic linear model (DLM) to the time series

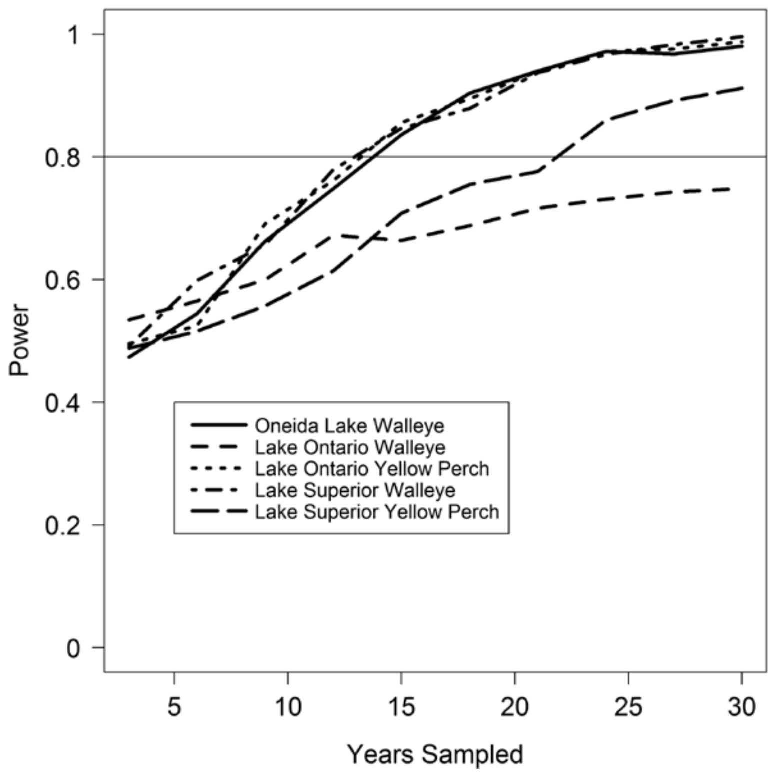


Figure 2. Power curves for detecting a 2% per year decline in species catch per effort for annual gillnet surveys in Oneida Lake, New York (Walleye only), the Wisconsin waters of Lake Superior (Walleye and Yellow Perch), and the Bay of Quinte in Lake Ontario (Walleye and Yellow Perch). Horizontal line at power = 0.8 was added as a reference.

of gillnet catches for Oneida Lake Walleye. The time series spanned the years 1957–2006 (except 1974 and 2005). Specifically, we fitted a DLM outlined in Panel 2. For this example, Bayesian estimation was performed using the program WinBUGS (WinBUGS 1.4; Spiegelhalter et al. 2003). An important feature of DLMs, which is relevant for addressing our monitoring objective, is that DLMs allow model coefficients (e.g., slope parameters) to change with time, enabling the elucidation of nonmonotonic trends.

The DLM considers both intra-annual (e.g., variation in CPE among sites within a year) and interannual (e.g., variation among years in average CPE) variability on Walleye CPE trends and captures the overall temporal dynamics of the Walleye CPE time series (Figure 3A). Note the increased uncertainty for the year 2006 (the final year of this time series), which is partly due to the missing data in 2005 and partly because the estimate is not constrained to be consistent with subsequent years of data. In addition, the Bayesian estimation allowed us to make inferences about changes to Walleye CPE relative to 1992. Specifically, negative annual rates of change occurred with a greater than 80% probability twice during the time series, one of which roughly overlaps with the period when the lake was experiencing zebra mussel establishment (Figure 3B, solid line). The results illustrate that the rate of temporal change likely changed over time.

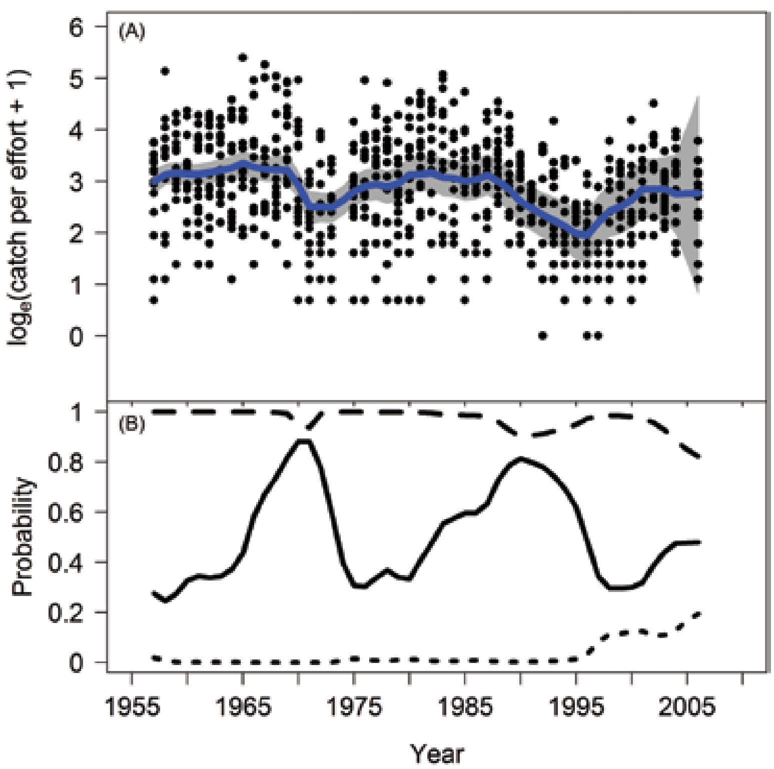


Figure 3. Posterior mean fitted values (curved solid line) and 95% credible intervals (shaded area) from a dynamic linear model fitted to log$_e$-transformed Walleye CPE from annual gillnet surveys (solid circles) from Oneida Lake, New York (Panel A). Panel B summarizes the estimated probability of annual rates of change <0 (i.e., probability of annual declines in CPE; solid line), >−0.25 (large dashed line), or >0.25 (small dashed line) occurring throughout the time series.

Summaries and inferences from a Bayesian analysis are straightforward. In particular, the posterior distributions of estimated parameters are easily summarized and thus can be used to address specific management objectives. For instance, if it was important in the Oneida Lake example for a management agency to know the probabilities of annual rates of change being outside of a specified value, then such summaries can quickly be obtained (Figure 3B, dashed lines for >−0.25 or >0.25).

DISCUSSION

Monitoring for temporal trends is an integral component of many fisheries management programs. What constitutes a management-relevant trend is not trivial and should be addressed within the broader decision-making process that, ultimately, will result in the implementation and evaluation of specific management actions. Ideally, this process will take place within a formal decision-making framework that includes appropriately diverse stakeholder groups from the onset, thereby defining what the problem is and why management action is required in the first place (Irwin et al. 2011). A transparent and inclusive approach to decision making will help ensure that all participants are aware of relevant monitoring objectives, such as the anticipated trend (i.e., duration and anticipated form; Panel 1) that is desired to be detected or if multiple types of temporal changes are important. Such a process will also help ensure reasonable expectations for the amount of time that may be necessary to detect a management-relevant trend. As we have illustrated across several sources, the statistical power to detect relatively subtle changes over time is often quite low for many freshwater fishery indicators.

As a result of this low statistical power environment, it may take 10 years or more to detect a small to moderate trend, which may be unacceptable to managers or stakeholders. For example, waiting 20 years to evaluate the effects of experimental length limits on a fishery would likely not garner much political support. This low statistical power does not suggest that biologists must necessarily wait a significant portion of their entire career to determine whether indices of interest have changed over time. In fact, if the assessment of management actions is the primary objective (e.g., versus detecting a sustained trend related to long-term changes in influential environmental conditions), then in addition to well-defined objectives, management experiments represent an alternative approach to routine monitoring that will potentially decrease the amount of time required to detect temporal trends.

Designed management experiments often include the monitoring of a reference or control site, in addition to the monitoring of the manipulated system. The use of control and manipulated systems can increase the rate at which we are able to learn about a system by providing additional evidence of how the manipulated system would be expected to have responded in the absence of the management action. Although a vari-

PANEL 2. DYNAMIC LINEAR MODELING.

Dynamic linear models (DLMs) are a class of state-space models. DLMs have several features that make them desirable for modeling fisheries-independent survey time series data, including (1) the estimated CPE at each year is related to the CPE at earlier years (Stow et al. 2004), which is consistent with temporal dynamics of fish populations; (2) time-varying parameters most strongly influenced the current year's information and data from other years closest in time, as opposed to traditional linear regression where parameters (i.e., slope and intercept) are influenced directly by all observations; and (3) DLMs easily accommodate missing and unequally spaced and missing data, which is common for fishery-independent survey data.

Dynamic linear models consist of observation and systems equations. Briefly, a DLM can be parameterized as follows:

Observation equation:

$$\log_e(\text{CPE})_{ti} = \text{level}_t + \psi_{ti}, \quad \psi_{ti} \sim N(0, \Psi_t) \qquad (1)$$

Systems equations:

$$\text{level}_t = \text{level}_{t-1} + \text{rate}_t + \omega_{t1}, \quad \omega_{t1} \sim N(0, \Omega_{t1}) \quad (2)$$

$$\text{rate}_t = \text{rate}_{t-1} + \omega_{t2}, \quad \omega_{t2} \sim N(0, \Omega_{t2}), \qquad (3)$$

where $\log_e(\text{CPE})_{ti}$ is the $\log_e$ of CPE (a small constant is typically added to accommodate zero catches) at site i in year t; level_t is the mean $\log_e$ (CPE) at time t; rate_t is the expected rate of change of mean $\log_e$ (CPE) and can be interpreted as the slope between consecutive time periods; and ψ_{ti} and ω_{tj} ($j = 1, 2$) are the error terms for year t sampled, which here are distributed as $N(0,\Psi_t)$ and $N(0,\Omega_{tj})$. In a Bayesian analysis, priors are needed for each estimated parameter, so to complete the model description we note that we assumed level_1, $\text{rate}_1 \sim N(0,1000)$; $1/\Omega^2_{tj} = \xi^{t-1} \cdot 1/\Omega^2_{1j}$, $1/\Psi^2_t = \xi^{t-1} \cdot 1/\Psi^2_1$ for $t > 1$ and $J = 1, 2$; and $1/\Omega^2_{1j}$, $1/\Psi^2_1 \sim \text{gamma}(0.001, 0.001)$, where ξ is a discount factor (between zero and one) representing the fact that older information in the time series is not as useful for forecasting (Sadraddini et al. 2011). The priors used on the initial year parameters are considered noninformative. Because individual gillnet sets (i.e., sample sites) were used as the response variable, as opposed to using annual mean CPE, this model accounts for both intra-annual (Ψ_t) and interannual variation ([Ω_{tj}]; see Lamon et al. [1998]; Congdon [2010]; and Sadraddini et al. [2011] for details).

ety of experimental designs can be implemented, before–after, control–impact paired designs (BACIP; Stewart-Oaten et al. 1986; Stewart-Oaten and Bence 2001) are often used. Under a BACIP design, experimental (manipulated) and control (reference) systems are monitored before and after the impact, which could be the implementation of a management action. In such management experiments, the reference site acts like a covariate and functions in a different way than the control of a randomized experiment (Stewart-Oaten et al. 1992; Bence et al. 1996). Paired sampling of the manipulated and reference sites during the period before the management action allows such predictions and estimation of the effect of the action. The simplest form of BACIP is just one approach to evaluating management experiments. The nature of spatial and temporal variability and the extent to which "before" sampling is possible influence appropriate sampling designs (e.g., Hewitt et al. 2001; Underwood and Chapman 2003; Hayes et al. 2003b; Paul 2011). In some cases, the existence of other covariates can even alleviate the need for before sampling at reference sites (Bence et al. 1996; Paul 2011). Regardless of the specifics, the more general point is that use of data other than the response data from the manipulated site can be used to develop a statistical model predicting the manipulated site in the absence of the manipulation and greatly reduce the time required to detect ecologically meaningful trends.

We also stress that our review of power analyses and our analyses of data on Great Lakes Percids must be viewed within the specific context they were meant to address: detecting long-term average trends. If monitoring objectives pertain to detecting short-term and/or nonmonotonic trends, then a power analysis based on linear regression may not produce the most relevant information. As illustrated with the DLM example, alternative analytical tools, combined with Bayesian inference, may provide a better match to management and monitoring objectives than linear models and null hypothesis testing. Therefore, when it seems likely that the rate of change is changing over time, we might expect that managers and stakeholders will often be more interested in a local (in time) rate of change. Additionally, we might become interested in how frequently the sustained directionality (i.e., positive or negative) of the rate of change is changing. DLM is an approach better suited for such situations and allows for useful inferences, whereas repeatedly applying standard linear regression to subsets of the data would likely increasingly suffer from reduced power. Analytical approaches that are able to provide a more flexible framework for linking management and monitoring objectives should also be able to contribute to designing monitoring programs and evaluating management actions.

In summary, statistical power analysis is one tool that is useful for the design of monitoring programs and experiments; however, fisheries managers work in high-variability, low-statistical-power environments. Decisions about temporal trends and expected future trajectories will be made regardless of low statistical power, so the question is "In the light of low power, what can we do to ensure that we make the best decision possible, given the data in hand?" A critical step is the formulation of monitoring objectives that include a statement defining what is meant by detecting temporal trend. The definition must be translated to an appropriate statistical model that maximizes the utility of subsequent inferences for informing the decision-making process. If null hypothesis testing is used as the inferential framework, communicating results from power analyses to develop realistic expectations about the time required to detect trends is essential to ensure legitimate assessments of management actions. In many cases, Bayesian inference may provide a reasonable alternative to traditional null hypothesis testing. Although changing the inferential framework does not necessarily increase our ability to detect trends over a shorter time frame, it does remove the constraint of a temporal trend being interpreted as significant or not significant. Rather, Bayesian inference forces explicit consideration of the ecologically and management-relevant effect sizes to be detected in addition to acceptable levels of uncertainty while providing the ability to make probabilistic statements about estimated parameters describing temporal trends that may facilitate communications with stakeholders.

ACKNOWLEDGMENTS

We thank the U.S. Fish and Wildlife Service Great Lakes Restoration Act for supporting this work and the Michigan Department of Natural Resources and the Pennsylvania Fish and Boat Commission for additional support. We also thank Mike Seider (WI DNR), Lars Rudstam (Cornell University), and Jim Hoyle (Ontario Ministry of Natural Resources) for providing the gillnet data and Weihai Liu for assistance in developing the estimation and simulation programs. We thank Lars Rudstam, Dan Dauwalter, Phil Bettoli and one anonymous reviewer for comments on this article. This article is contribution number 2013-03 of the Quantitative Fisheries Center at Michigan State University. Use of trade names does not imply endorsement by the federal government.

REFERENCES

Al-Chokhachy, R., P. Budy, and M. Conner. 2009. Detecting declines in the abundance of a Bull Trout (*Salvelinus confluentus*) population: understanding the accuracy, precision, and costs of our efforts. Canadian Journal of Fisheries and Aquatic Sciences 66:649–658.

Anlauf, K. J., W. Gaeuman, and K. K. Jones. 2011. Detection of regional trends in salmonid habitat in coastal streams, Oregon. Transactions of the American Fisheries Society 140:52–66.

Baker, M. E., and R. S. King. 2010. A new method for detecting and interpreting biodiversity and ecological community thresholds. Methods in Ecology and Evolution 1:25–37.

Bence, J. R., A. Stewart-Oaten, and S. C. Schroeter. 1996. Estimating the size of an effect from a before–after–control–impact-pairs design: the predictive approach applied to a power plant study. Pages 133–149 *in* R. J. Schmitt and C. W. Osenberg, editors. Detecting ecological impacts: concepts and applications in coastal habitats. Academic Press, San Diego, California.

Brenden, T. O., L. Wang, and S. Zhenming. 2008. Quantitative identification of disturbance thresholds in support of aquatic resource management. Environmental Management 42:821–832.

Carpenter, S. R. 2003. Regime shifts in lake ecosystems: pattern and variation, volume 15. Ecology Institute, Oldendorf/Luhe, Germany.

Carpenter, S. R., J. J. Cole, M. L. Pace, R. Batt, W. A. Brock, T. Cline, J. Coloso, J. R. Hodgson, J. F. Kitchell, D. A. Seekell, L. Smith, and B. Weidel. 2011. Early warnings of regime shifts: a whole-ecosystem experiment. Science 332:1079–1082.

Congdon, P. D. 2010. Applied Bayesian hierarchical methods. CRC Press/Chapman & Hall, Boca Raton, Florida.

Dauwalter, D. C., F. J. Rahel, and K. G. Gerow. 2009. Temporal variation in Trout populations: implications for monitoring and trend detection. Transactions of the American Fisheries Society 138:38–51.

———. 2010. Power of revisit monitoring designs to detect forestwide declines in Trout populations. North American Journal of Fisheries Management 30:1462–1468.

Ellison, A. M. 2004. Bayesian inference in ecology. Ecology Letters 7:509–520.

Fabricius, K. E., and G. De'ath. 2004. Identifying ecological change and its causes: a case study on coral reefs. Ecological Applications 14:1448–1465.

Gallagher, S. P., D. W. Wright, B. W. Collins, and P. B. Adams. 2010. A regional approach for monitoring salmonid status and trends: results from a pilot study in coastal Mendocino County, California. North American Journal of Fisheries Management 30:1075–1085.

Hayes, D., E. Baker, R. Bednarz, D. Borgeson, Jr., J. Braunscheidel, A. Harrington, R. Hay, J. Waybrant, J. Breck, A. Nuhfer, M. Bremigan, R. Lockwood, J. Schneider, P. Seelbach, and T. Zorn. 2003a. Developing a standardized sampling program: the Michigan experience. Fisheries 28:18–25.

Hayes, D. B., J. R. Baylis, L. M. Carl, H. Dodd, J. Goldstein, R. L. McLaughlin, D. L. G. Noakes, and L. Porto. 2003b. Biological effect of low-head Lamprey barriers: designs for extensive surveys and the value of incorporating intensive process-oriented research. Journal of Great Lakes Research 29(Supplement 1):373–385.

Hewitt, J. E., S. E. Thrush, and V. J. Cummings. 2001. Assessing environmental impacts: effects of spatial and temporal variability at likely impact scales. Ecological Applications 11:1502–1516.

Irwin, B. J., L. G. Rudstam, J. R. Jackson, A. J. VanDeValk, and J. L. Forney. In press. Long-term trends in the fish community of Oneida Lake: analysis of the zebra mussel invasion. Submitted to L. G. Rudstam, E. L. Mills, J. R. Jackson, and D. J. Stewart, editors. Oneida Lake: Long-term Dynamics of a Managed Ecosystem and its Fisheries. American Fisheries Society. Bethesda, MD.

Irwin, B. J., L. G. Rudstam, J. R. Jackson, A. J. VanDeValk, J. L. Forney, and D. G. Fitzgerald. 2009. Depensatory mortality, density-dependent growth, and delayed compensation: disentangling the interplay of mortality, growth, and density during early life stages of Yellow Perch. Transactions of the American Fisheries Society 138:99–110.

Irwin, B. J., T. J. Treska, L. G. Rudstam, P. J. Sullivan, J. R. Jackson, A. J. VanDeValk, and J. L. Forney. 2008. Estimating Walleye (*Sander*

vitreus) density, gear catchability, and mortality using three fishery-independent data sets for Oneida Lake, New York. Canadian Journal of Fisheries and Aquatic Sciences 65:1366–1378.
Irwin, B. J., M. L. Wilberg, M. L. Jones, and J. R. Bence. 2011. Applying structured decision making to recreational fisheries management. Fisheries 36:113–122.
Lamon, E. C., S. R. Carpenter, and C. A. Stow. 1998. Forecasting PCB concentrations in Lake Michigan salmonids: a dynamic linear model approach. Ecological Applications 8:659–668.
Larsen, D. P., P. R. Kaufmann, T. M. Kincaid, and N. S. Urquhart. 2004. Detecting persistent change in the habitat of Salmon-bearing streams in the Pacific Northwest. Canadian Journal of Fisheries and Aquatic Sciences 61:283–291.
Larsen, D. P., T. M. Kincaid, S. E. Jacobs, and N. S. Urquhart. 2001. Designs for evaluating local and regional scale trends. BioScience 51:1069–1078.
Lindenmayer, D. B., and G. E. Likens. 2010. The science and application of ecological monitoring. Biological Conservation 143:1317–1328.
Lyons, J. E., M. C. Runge, H. P. Laskowski, and W. L. Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. The Journal of Wildlife Management 72:1683–1692.
Maxell, B.A. 1999. A power analysis on the monitoring of bull trout stocks using redd counts. North American Journal of Fisheries Management 19:860–866.
Murphy, B. R., and D. W. Willis, editors. 1996. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.
Paul, W. L. 2011. A causal modelling approach to spatial and temporal confounding in environmental impact studies. Environmetrics 22:626–638.
Roper, B. B., J. L. Kershner, E. Archer, R. Henderson, and N. Bouwes. 2002. An evaluation of physical stream habitat attributes used to monitor streams. Journal of the American Water Resources Association 38:1637–1646.
Rudstam, L. G., T. E. Brooking, S. D. Krueger, J. R. Jackson, and L. Wetherbee. 2011. Analysis of compensatory responses in landlocked alewives to Walleye predation: a tale of two lakes. Transactions of the American Fisheries Society 140:1587–1603.
Rudstam, L. G., A. J. VanDeValk, C. M. Adams, J. T. H. Coleman, J. L. Forney, and M. E. Richmond. 2004. Cormorant predation and the population dynamics of Walleye and Yellow Perch in Oneida Lake. Ecological Applications 14(1):149–163.
Sadraddini, S., M. E. Azim, T. Shimoda, S. P. Bhavsar, K. G. Drouillard, S. M. Backus, and G. B. Arhonditsis. 2011. A Bayesian assessment of the PCB temporal trends in Lake Erie fish communities. Journal of Great Lakes Research 37: 507-520.
Spiegelhalter, D. J., A. Thomas, N. G. Best, and D. Lunn. 2003. WinBUGS. Version 1.4. User manual. MRC Biostatistics Unit, Cambridge, England.
Stewart-Oaten, A., and J. R. Bence. 2001. Temporal and spatial variation in environmental assessment. Ecological Monographs 71:305–339.
Stewart-Oaten, A., J. R. Bence, and C. W. Osenberg. 1992. Assessing effects of unreplicated perturbations: no simple solutions. Ecology 73:1396–1404.
Stewart-Oaten, A., W. W. Murdoch, and K. R. Parker. 1986. Environmental impact assessment: “pseudoreplication” in time? Ecology 67:929–940.
Stow, C. A., E. C. Lamon, S. S. Qian, and C. S. Schrank. 2004. Will Lake Michigan lake trout meet the Great Lakes strategy 2002 PCB reduction goal? Environmental Science and Technology 38:359–363.
Thomson, J. R., W. J. Kimmerer, L. R. Brown, K. B. Newman, R. M. Nally, W. A. Bennett, F. Feyrer, and E. Fleishman. 2010. Bayesian change point analysis of abundance trends for pelagic fishes in the upper San Francisco Estuary. Ecological Applications 20:1431–1448.
Underwood, A. J., and M. G. Chapman. 2003. Power, precaution, type II error and sampling design in assessment of environmental impacts. Journal of Experimental Marine Biology and Ecology 296:49–70.
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 4:404–414.
Urquhart, N. S., S. G. Paulsen, and D. P. Larsen. 1998. Monitoring for policy-relevant regional trends over time. Ecological Applications 8:246–257.
Wade, P. R. 2000. Bayesian methods in conservation biology. Conservation Biology 14:1308–1316.
Wagner, T., J. R. Bence, M. T. Bremigan, D. B. Hayes, and M. J. Wilberg. 2007. Regional trends in fish mean length at age: components of variance and the power to detect trends. Canadian Journal of Fisheries and Aquatic Sciences 64:968–978.
Wagner, T., C. S. Vandergoot, and J. Tyson. 2009. Evaluating the power to detect temporal trends in fishery-independent surveys: a case study based on gillnets set in the Ohio Waters of Lake Erie for Walleye. North American Journal of Fisheries Management 29:805–816.