International Council for the Exploration of the Sea

C.M. 1993/D:35
Ref. M
Statistics Committee

Two Randomization Tests for Estimation of Regional Changes in Fish Abundance Indices: Application to North Atlantic Salmon

Paul J. Rago
Northeast Fisheries Science Center
National Marine Fisheries Service
Woods Hole, MA 02543

ABSTRACT

Randomization tests are proposed as a general procedure for analyzing composite trends in fish population indices. Two randomization tests are developed in this paper. The first test allows inferences to be made about the composite trend for multiple sites. Composite trend is estimated as a weighted average of the slopes of log transformed count data versus time. Let $Y_{k,t}$ = abundance index at site k and time t. Counts are modeled as $\log_e[Y_{k,t} + c] = a_k + b_k\ t + \log_e[e_{k,t}]$ where a_k and b_k are the intercept and slope terms, respectively for site k and $e_{k,t}$ is the error term. An aggregate measure of the slope for k=1, 2, ..., K sites is estimated as a weighted average of the b_k:

$$B_o = \frac{\sum_{k=1}^{K} W_k\, b_k}{\sum_{k=1}^{K} W_k}$$

where $W_k = Z_k \,/\, \mathrm{Var}(b_k)$, Z_k is the back transformed predicted mean of the fitted regression, i.e., $Z_k = \exp(\hat{a}_k + \hat{b}_k\ \bar{t}\,)$, and t is the mean year for the time series. The above model has been widely applied by North American and European avian biologists. A robust smoothing procedure known as locally weighted regression scatter plot smoothing is recommended as an approach for identifying appropriate temporal windows $\{t_{min}, t_{max}\}$ and grouping of sites.

The second test addresses a related problem of estimating a point change in population status as a result of some intervention, say a change in fishery regulations. In many instances the time periods for the baseline and treatment periods may be short owing to multiple interventions over time. As an example, frequently changing fishing regulations may make it difficult to achieve the stationarity necessary for application of intervention analysis techniques of Box and Tiao(1975). Alternatively, a randomization test can be applied to any function of the data (e.g., ratio of means) in the baseline and treatment periods. If the number of observations in the baseline and treatment periods are m and n, respectively, the

ratio of means can be defined as:

$$R_o = \frac{\sum_{k=1}^{K} \sum_{t=m+1}^{m+n_k} \frac{Y_{k,t}}{n_k}}{\sum_{k=1}^{K} \sum_{t=1}^{m_k} \frac{Y_{k,t}}{m_k}}$$

The sampling distributions of $\mathbf{B}_o$ and $\mathbf{R}_o$ are enumerable, but can be approximated by randomizing the count data for each site and computing a new value of **B** and **R** for each iteration. The probability of obtaining the original observed value $\mathbf{B}_o$ or $\mathbf{R}_o$ can be approximated by direct comparison with the sampling distributions of **B** or **R** , respectively.

Randomization tests are useful for assessing changes in stock status because such tests require few assumptions, the results are readily interpretable, and the sampling distribution of the test statistic can be easily approximated on a portable computer. To illustrate the utility of the randomization tests, the methods are applied to Atlantic salmon count data for rivers in Atlantic Canada summarized in the North Atlantic Salmon Working Group of ICES.

INTRODUCTION

One of the common problems faced by fishery biologists is the assessment of population trends. Of the many techniques available to evaluate long term trends, the Box-Jenkins time series models (Box and Jenkins 1970) have been successfully applied to menhaden (Jensen 1976), oysters (Ulanowicz et al. 1980), rock lobster (Saila et al. 1980), and haddock (Pennington 1985). Long term time series, however, are the exception rather than the rule in fisheries assessment. Changes in management, fishing effort, or environmental conditions can act singly or together to confound the interpretation of long term time series. Analyses of long term data is instructive, but detection of recent trends (< 10 yr) and responses of populations to management interventions are often more immediate management concerns. Other methods of assessment are necessary when the number of observations is small or when assumptions are difficult to test.

For many fish species, and Atlantic salmon in particular, one or more indices of abundance are routinely collected at widely distributed sites under a wide variety of conditions. If such monitoring programs are part of an overall scientific sampling program, sampling theory can be applied and the ability to detect change is governed by the precision of the survey. When species are distributed widely across regions or countries, scientific surveys are difficult to implement. Nonetheless, specific studies tend to be consistent across years, allowing within series comparisons. Comparisons among series, however, can be hampered by varying methodologies and unknown biases. Under these circumstances, randomization tests can be used to make inferences about population status.

Randomization tests were first proposed by Fisher (1935) but widespread application has been stimulated by the availability of microcomputers. More recent treatment of the theory may be found in Lehmann (1975); recent applications may be found in Soms (1977), Rosenbaum(1988), Raz (1989), Manly (1991), and Raz and Fein (1992). Randomization tests utilize the information contained in the temporal order of the data without making unrealistic assumptions about the error distribution. Randomization tests are particularly well suited for assessing changes in stock status because such tests require few assumptions, the results are readily interpretable, and the sampling distribution of the test statistic can be easily approximated on a portable computer.

Circumstances that confound the interpretation of index data for salmon and other fish species are germane to other wildlife populations. Avian biologists have recently developed techniques for assessment of avian abundance (Sauer and Droege 1990) which emphasize the use of graphical techniques for exploratory data analyses and "route regression analysis". Route regression analysis has been used to assess avian population trends over broad geographical regions (Geissler and Noon 1981; Geissler 1984). "Route" typically refers to a time series of bird counts at a particular site. A collection of "routes" along broad geographical region constitutes a flyway. Route regression analysis uses a general linear model to adjust count data for observer bias and to estimate within-route variability. A composite estimate of trend is developed and jackknifing or bootstrapping techniques are employed to estimate its variance (Geissler and Sauer 1990). Alternatively, Collins (1990) has recommended the use of re-randomization to approximate the sampling distribution of the composite slope estimate.

In this paper I apply the general class of route regression models to Atlantic salmon data, utilizing the randomization approach of Collins (1990). I then develop a complementary model based on the ratio of means between a baseline and treatment period for multiple time series. The statistical power of this ratio test is examined with simulated data. Both models are applied to estimated returns of Atlantic salmon to monitored rivers in Canada. Microcomputer software to apply these models has been written and is available upon request.

METHODS

Graphical Approaches

Analysis of time-series data for trends can be envisioned as three distinct steps: identification, grouping, and hypothesis testing. Identification and grouping can be facilitated with robust smoothing approaches (Hippel and McLeod 1989, Raz 1989, Taub 1990, James et al. 1990).

Identification is the process by which the underlying signal (e.g., trend or cycles) is distinguished from the noise (i.e. random error). Autocorrelation and differencing methods (Box and Jenkins 1970; Nelson 1973) may have limited utility when time series are short in duration or have missing values. Tests of stationarity and normality assumptions will typically have low power under these circumstances. Statistical smoothing procedures do not make strong assumptions about the underlying distribution of error terms. Smoothing is especially useful when detection of short term trends is important. Recently developed graphical methods (Chambers et al. 1983) have a strong theoretical basis and allow for visual examination of short and long term trends. LOWESS, the acronym for "locally weighted regression scatter plot smoothing" (Cleveland 1979), techniques fall into the general category of "robust" statistical procedures which, in general terms, are resistant to outliers. Other smoothing approaches such as kernel estimation (Gasser and Muller 1979) or smoothing splines (Silverman 1985) could be used.

When it is desirable to make inferences about broad geographical regions, LOWESS smoothing can also assist in the identification of systems with similar behavior and facilitate grouping. When two systems are behaving similarly over some time interval, a LOWESS pairwise plot of one times series against another will have straight line segments. During time periods in which two time series have divergent responses, the LOWESS plot will be erratic. Similar behavior among time series suggests, but does not confirm, similar underlying factors and may aid in identifying causative factors. More formal statistical models for grouping such as cluster analysis or principal components analysis could be applied but robust graphical techniques are suggested as the appropriate first step.

Identification and grouping suggest appropriate time intervals and combinations of systems (populations) which can then be examined with route regression analysis or the ratio test described below. All graphs were prepared using SYGRAPH (Wilkinson 1990a), which is part of the general statistical package SYSTAT (Wilkinson 1990b).

Model Description: Route Regression

The objective of route regression is to make a probabilistic statement about the composite trend for some subset of the populations under consideration. Consider a set of count data in which $Y_{k,t}$ denotes the count of fish at site k and time t.

$$(Y_{k,t}) = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,t_{min}} & Y_{1,t_{min+1}} & \cdots & Y_{1,t_{max}} & \cdots & Y_{1,m+n} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,t_{min}} & Y_{2,t_{min+1}} & \cdots & Y_{2,t_{max}} & \cdots & Y_{2,m+n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{K,1} & Y_{K,2} & \cdots & Y_{K,t_{min}} & Y_{K,t_{min+1}} & \cdots & Y_{K,t_{max}} & \cdots & Y_{K,m+n} \end{bmatrix}$$

Suppose we are interested in drawing inferences about the composite trend in abundance for K sites over some subinterval $\{t_{min}, t_{max}\}$ within the range $t=1, 2, \ldots, T$; where $T = m+n$. A general statistical model for count data $Y_{k,t}$ is of the form

$$Y_{k,t} = a_k \, e^{b_k t} \, \epsilon_{k,t} \tag{1}$$

where a_k and b_k are constants for site k and $\epsilon_{k,t}$ is the error term. The multiplicative error structure reflects the common phenomena whereby the variance exceeds the mean and increases with it. Transformations are often necessary to stabilize the variance and to more closely meet the assumptions of general linear models (Neter et al. 1990). Although there is much literature on the subject of statistical transformations (e.g. Box and Cox 1964), the most commonly used transformation for count data is of the form $\log_e(Y + c)$ where c is some constant. A simulation study of count data by Collins (1990) suggested that $c=0.23$ would yield the greatest probability of correctly detecting both short (5 yr) and long term (20 yr) trends. Collins' conclusions were based on random samples drawn from a negative binomial model with different mean densities and different levels of the aggregation parameter γ. In lieu of a similar study for fish counts, a value of $c=0.23$ is used herein. The transformed linear model corresponding to Eq. 1 is
The next step in route regression is to obtain an estimate of the overall trend (**B**) among the

$$\log_e[Y_{k,t} + 0.23] = \log_e(a_k) + b_k t + \log_e[\epsilon_{k,t}] \qquad (2)$$

K sites. Estimates of b_k over the time interval t_{min} to t_{max} are obtained via Eq. (2); missing data with a time range can be incorporated into the estimate of b_k. Temporal variability and the magnitude of the time series have important implications for the detectability of the true underlying trend. Simple averaging of regression slope parameters would be appropriate only if all of the systems had equal temporal variability and all time series were similar in magnitude (i.e., $a_1 = a_2 = \ldots = a_K$). A basic tenet in route regression is that slope estimates are weighted inversely by their variance and proportionally by the magnitude of the series.

Avian biologists (Geissler and Noon 1981; Geissler 1984, Collins 1990) have proposed a weighted average estimator of **B**

$$B_o = \frac{\sum_{k=1}^{K} W_k b_k}{\sum_{k=1}^{K} W_k} \qquad (3)$$

where $W_k = Z_k / \mathrm{Var}(b_k)$. Collins (1990) recommends estimating Z_k as the back transformed predicted mean of the fitted regression from Eq. 2. Thus

$$Z_k = e^{[\hat{a}_k + \hat{b}_k \bar{t}]} \qquad (4)$$

where t is the mean year for the time series. Several measures of the variance of the slope have been proposed (Geissler and Noon 1981, Robbins et al. 1986, Geissler 1984) but Collins (1990) noted that $\mathrm{Var}(b_k)$ can be unreliable when the number of observations are small. James et al. (1990) recommend additional work on this aspect of route regression analysis.

Statistical inferences about the observed value of **B** can be made by approximating its sampling distribution using bootstrap and jackknife techniques (Geissler and Sauer 1990) or re-randomization (Collins 1990). In a randomization model the problem is stated as, "Under the null hypothesis that the observations ($Y_{k,t}$) are randomly ordered within each series, what is the probability of obtaining a value of **B** greater than or equal to the observed $\mathbf{B_o}$?" In other words, is the observed time series simply a random ordering of observations or is the observed value unlikely? If the observed value is unlikely, then it may provide evidence of a true change in the underlying process.

The randomization approach allows us to quantify how unlikely $\mathbf{B_o}$ is by approximating its sampling distribution. Each time series $Y_{k,t}$ is randomly shuffled and a new $\hat{b}_{k,i}$ estimate is obtained, where the i refers to the i-th of realization for the k-th series. The weighted mean slope for each realization is denoted as $\mathbf{B}_i$. The process is repeated an arbitrarily large number of times, say N, for each of the K time series and the sampling distribution **B** is approximated by the set of $\mathbf{B}_i$. The probability level associated with the observed **B** is simply the number of $\mathbf{B}_i < \mathbf{B}$ divided by N.

Model Description: Ratio Test

A related problem to route regression concerns changes in mean abundance between two periods of time. The first period of time is called the baseline period and consists of m years (t=1, 2, ...m); the second period is the treatment period consisting of n years (t=m+1, m+2, ...m+n). The general data matrix for these problems can be written as

$$(Y_{k,t}) = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,m} & Y_{1,m+1} & Y_{1,m+2} & \cdots & Y_{1,m+n} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,m} & Y_{2,m+1} & Y_{2,m+2} & \cdots & Y_{2,m+n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{K,1} & Y_{K,2} & \cdots & Y_{K,m} & Y_{K,m+1} & Y_{K,m+2} & \cdots & Y_{K,m+n} \end{bmatrix}$$

Consider a simple example in which one wants to compute the ratio of means between two periods of time. For a single series k the ratio of the means for these two periods can be estimated as

$$R_o = \frac{\sum_{t=m+1}^{m+n} \frac{Y_t}{n}}{\sum_{t=1}^{m} \frac{Y_t}{m}} \qquad (5)$$

Usual t-tests could be used to draw inference for such a problem, but testing assumptions of independence of observations and equality of variances might be difficult, especially when n=1. Here again, randomization tests can be used to approximate the sampling distribution of $\mathbf{R}_o$.

For any single time series the number of possible orderings is obtained as the combinatorial of m+n with n. For K time series the number of possible orderings increases with the number of time series such that the enumeration of the sampling distribution of $\mathbf{R}_o$ consists of

Q possible observations where

$$Q = \binom{m+n}{n}^{K} \tag{6}$$

In general terms, the resolution of the test (i.e., one over the number of possible outcomes is determined by 1/Q. As the number of time series increases, the resolving power of the test can become very fine if ties or missing values do not predominate the time series $Y_{k,t}$. In practice the sampling distribution of $\mathbf{R}_o$ can be approximated by generating a subsample of 1000 or more $\mathbf{R}_i$ using randomization procedures.

The simple model in Eq. 5 can be generalized to K time series as follows

$$R_o = \frac{\sum_{k=1}^{K}\sum_{t=m+1}^{m+n_k}\frac{Y_{k,t}}{n_k}}{\sum_{k=1}^{K}\sum_{t=1}^{m_k}\frac{Y_{k,t}}{m_k}} \tag{7}$$

The advantage of formulating the ratio as in Eq . 7 is that large counts contribute more to the ratio than small counts. Note also that $m_k \leq m$, and that $n_k \leq n$. The values m_k and n_k will equal m and n except when missing values are present.

<u>Statistical Power of Ratio Test</u>

The statistical power (i.e., the probability of correctly identifying a true change) of the ratio test was evaluated with simulated data. Simulations for power calculations assumed that the underlying count data $Y_{k,t}$ were distributed as negative binomially distributed random variables. The following parameterization of the negative binomial distribution by Bliss and Owen (1958) was used:

$$P[Y = y] = \frac{\Gamma(y+\gamma^{-1})}{y!\,\Gamma(\gamma^{-1})}\left(\frac{\gamma\,\mu}{1+\gamma\,\mu}\right)(1+\gamma\,\mu)^{-1/\gamma} \tag{8}$$

where the parameters μ_k and γ represent the mean and dispersion parameters, respectively. The expected value of $Y_k = E[Y_k,t] = \mu_{k,t}$ and the variance of $Y_{k,t} = V[Y_{k,t}] = \mu_{k,t} + \gamma(\mu_{k,t})^2$. . . The dispersion parameter γ was set equal to 1/10. As the gamma function $\Gamma(x+1)$ for integers simplifies to x! (Mood et al. 1974) and Eq. 8 simplifies to

$$P[Y=y] = \frac{(y+\gamma^{-1}-1)!}{y!\ (\gamma^{-1}-1)!} \left(\frac{\gamma\ \mu}{1+\gamma\ \mu}\right) (1+\gamma\ \mu)^{-1/\gamma} \tag{9}$$

Pseudo-random numbers were generated from the negative binomial distribution were generated using the method described by Piegorsch (1992) . The following equation was solved for the minimum value of J that satisfies the inequality .

$$u \le \sum_{x=\kappa}^{J} \binom{x-1}{\kappa-1} (1+\gamma\ \mu)^{-\kappa} \left(\frac{\gamma\ \mu}{1+\gamma\ \mu}\right)^{x-\kappa} \tag{10}$$

where u is a uniform (0,1) random number, $\kappa = \gamma^{-1}$, and γ is restricted to integer values. The negative binomial random number y equals J-κ.

Two aspects of power were considered. First, the effects of adding additional time series were investigated by letting K vary from 1 to 11 by increments of 2. The baseline period was assumed to have eight years (i.e., m=8) of observations while the treatment period consisted of 2 years (i.e., n=2). Changes in the underlying mean for the treatment period were modeled as

$$\mu_{k,t} = \begin{cases} \mu & \text{for } k=1,\ldots,m \\ \mu+\delta\ \mu & \text{for } k=m+1,\ \ldots\ ,m+n \end{cases} \tag{11}$$

To investigate the ability of the estimator to correctly detect increases and decreases in the mean I let δ = 1.1, 1.1^{-1}, 1.25 and 1.25^{-1}.

The second aspect of power was the ability of the ratio test to detect changes of magnitude δ for a fixed number of series (K=5) and a "typical" set of baseline means μ_k = {1250, 625, 500, 300, 50}. The baseline means were arbitrarily chosen to span two orders of magnitude. The step change parameter δ was set to 1.1, 1.2, 1.3, 1.4, 1.5, 1.75, 2, and 1.1^{-1}, 1.2^{-1}, 1.3^{-1}, 1.4^{-1}, 1.5^{-1}, 1.75^{-1}, 2^{-1}.

Application of Route Regression to Counts of Small Salmon at Index Rivers in Canada

Since 1984 Canada has imposed a series of increasingly restrictive management measures on Atlantic salmon fisheries, culminating with the closure of fisheries in insular Newfoundland in 1992 (Friedland 1993). The North Atlantic Salmon Working Group (Anon 1993, Table 2.2.3.1, Fig. 3.3.1.3) graphically summarized count data for "small" salmon in 21 rivers in Atlantic Canada using smoothed Z-scores. Small salmon are fish less than 63 cm length and typically, fish which return after one year at sea. Rivers were clustered into 6 geographical regions with 3 or 4 rivers in each. To quantify the composite trend in each of these regions I applied the route regression model to the 1984-1992 count data listed in Table 1. Data were analyzed using the computer program ROUTE.EXE (available upon request).

Application of Ratio Test to Returns of Small and Large Salmon to Newfoundland.

The ratio test was applied to the estimated returns of small and large salmon to selected Newfoundland rivers during the period 1987 to 1992. The purpose of the test was to determine whether the closure of fisheries in insular Newfoundland in 1992 had any effect on returns of small and large salmon to the Humber River, Rocky River, Terra Nova, Middle Brook, Biscay Bay, Northeast River (Placentia) and the Conne River (Table 2). "Large" salmon exceed 63 cm in length and comprise multi-sea winter adults and repeat spawners. For both groups, 1992 observations were compared to the 1987-1991 mean. Data for small and large returns were analyzed separately using the computer program NPRATIO.EXE (available upon request).

RESULTS

Application of Route Regression to Counts of Small Salmon at Index Rivers in Canada

Route regression analysis of count data for small suggested a variety of trends by region (Fig. 1) In southern Newfoundland counts of small salmon have decreased significantly over the time period ($P<0.0002$, Table 3). The decline in the Conne River dominates the estimate of composite trend for this region. In contrast, no significant trend was evident in 3 western Newfoundland rivers ($P=0.4760$) or 4 eastern Newfoundland rivers ($P=0.784$). Moving to the north shore region of Quebec, counts of small salmon also revealed no significant trend ($P=0.1982$) over the 1984 to 1992 period. No significant trend was estimated for Scotia-Fundy Rivers ($P=0.6344$) during this period. Small salmon in the large rivers of the Gulf Region, particularly the Miramichi River, appear to have increased significantly during this period ($P=0.0458$).

Application of Ratio Test to Returns of Small and Large Salmon to Newfoundland.

Results of the nonparametric ratio test suggest that the probability of the observed ratio of 1.46 in small salmon returns is about 13% (Table 4). Thus we would fail to reject null hypothesis and conclude that no significant increase in small salmon returns had occurred. In contrast the observed ratio for large salmon of 3.91 had a probability level of 0.035 (Table 4). Thus we would conclude that large salmon returns were significantly higher in 1992. Presumably, the increase in returns of large salmon was attributable to cessation of coastal fisheries in Newfoundland. As the coastal fishery has been closed for only one year continued monitoring should improve the statistical power to detect changes in abundance.

Power Analyses of Ratio Test

Results of the power analyses illustrated the expected increase in power as additional sites were added to the analysis and decrease in power for smaller acceptable levels of Type I statistical error (α) (Fig. 2). The ability to correctly identify increases in the mean of 10% (Fig. 2a) was less than 60%, even when 11 sites were considered and α was set to 0.20. At more commonly used α levels (0.05, 0.01) the nonparametric test would have a power less than 30%. In contrast an increase in the mean level of 25% could be correctly detected 60% of the time when 7 or more sites were examined and $\alpha = 0.05$ (Fig. 2b). Similar conclusions apply to decreases in the mean of comparable magnitudes (i.e., 1.1^{-1} and 1.25^{-1}, Fig. 2c, and 2d, respectively) .

To explore the ability of the test to detect varying magnitudes of percentage change I computed the power for step increases ranging from 10% to 100% and decreases from 9 to 50% (Fig. 3). The plot reveals the symmetry of power estimates for increases of a given magnitude or its reciprocal. For the assumed configuration of 5 sites, 8-year baseline period and 2-yr treatment period, the nonparametric ratio model could detect changes of 40% or more 80% of the time with only a 5% chance of incorrectly rejecting the null hypothesis of no change. Acceptance of a greater Type I error level would increase the power substantially (Fig 3) .

DISCUSSION

The proposed randomization models appear to be useful for drawing inferences about regional trends and step changes in abundance for fish populations. The example applications for Atlantic salmon counts allow probability statements to be made about broad geographical regions. The lack of consistency in the 9 year trends among regions may be indicative of varying life history and migration patterns (Table 3). Difference in significance levels for changes in mean abundance of small and large salmon in 1992 (Table 4) may reflect increased variability of small salmon counts. An appraisal of the potential causes for the variations among geographic regions or size groups is beyond the scope of this paper. Additional biological information is necessary to properly interpret potential mechanisms of change in these groups. The randomization models however, provide interesting starting points for evaluation of hypotheses.

Conservation of fishery resources demands that downward trends be detected early so that management measures can be taken. Identification of long term cycles is useful for retrospective analyses but prior cyclic behavior does not guarantee that a decimated contemporary population will rebound to earlier highs. Thus, detection of trends over periods of less than a decade is important. In a similar fashion, it's important to detect the effects of management actions on population status, particularly when conservation measures incur considerable expense.

The randomization models are conceptually simple and their apparent statistical power for simulated data (Fig. 2, 3) is encouraging. Similar calculations with actual data could be used for estimating least detectable rates of change. For example, suppose that m baseline years are available for K sites and one is interested in the magnitude of change that would be detectable in n subsequent years. Random data sets could be constructed in which the n values are randomly selected from the m observations at the k-th site. Each randomly selected value would be multiplied by δ and the significance level for the derived critical value R_0 of the appended data set of m+n observations could be estimated. The number of times that the null hypothesis was correctly rejected would be a measure of the power of the test. Hence power analyses could aid in the design and evaluation of management experiments.

Power analyses for the route regression model were not conducted. Titus et al. (1990) have recognized this as an important area of research. Simulation studies of Geissler and Sauer (1990) suggested that trend estimates based on less than 5 years of data may be biased. Therefore caution should be exercised when applying the model to short time series.

Both the route regression and ratio randomization models could be expanded to consider non-count data. The units of measure among sites should be commensurate and alternative weighting factors (W_k) would be employed. For example, mean lengths of fish at different sites might be investigated for evidence of changes in growth rates or gear selectivity over time. Weighting factors could simply be the sample size for each site, the stratum size, or total catches within a stratum or site. As noted earlier, the choice of weighting factors is an active area of current research in avian biology applications of route regression. Application of the randomization tests to time series with non-commensurate units should be done cautiously. Observations within each site k could be standardized but selection of weighting factors could strongly affect the outcome of the test.

Trend analyses in other areas of environmental science (e.g., Anon. 1991) should also be reviewed for potential application to fish population assessment. Raz (1989) has recently extended the theory for repeated measures designs by incorporating randomization and smoothing components. His results show that smoothing increased the power of the tests for time effects and group by time interactions. Nonparametric smoothing approaches have been advocated by Taub (1990) and James et al. (1990) for analysis of bird populations, Hippel and McLeod (1989) for water quality data. The generalized additive models of Hastie and Tibshirani (1990) illustrates the generality of smoothing for assessment of a broad class of problems. Finally, the randomization models described by Manly (1991) should find general applicability to fisheries science.

REFERENCES

Anon. 1991. Report of the Working Group on Statistical Aspects of Trend Monitoring. International Council for the Exploration of the Sea. Copenhagen. C.M. 1991/POLL: 2.

Anon. 1993. Report of the Working Group on North Atlantic Salmon. International Council for the Exploration of the Sea. 5-12 March 1993, Copenhagen. Doc. C.M. 1993/Assess:10.

Bliss, C. I. and A. R. G. Owen. 1958. Negative binomial distributions with common k. Biometrika 45:37-58.

Box, G.E.P. and G. C. Tiao 1975. Intervention analysis with applications to economic and environmental problems. Journal of the American Statistical Association 70:70-79.

Box, G. E. P. and D. R. Cox. 1964. An analysis of transformations. Journal of the Royal Statistical Society B 26:211-252.

Box, G. E. P. and G. M. Jenkins. 1970. Time series analysis, forecasting and control. Holden-Day, Inc., San Francisco, CA, USA

Chambers, J. M., W. S. Cleveland, B. Kleiner, and P. A. Tukey. 1983. Graphical methods for data analysis. Duxbury Press, Boston, MA, USA.

Cleveland, W. S. 1979. Robust locally-weighted regression and smoothing scatter plots. Journal of the American Statistical Association 74:829-836.

Collins, B. T. 1990. Using rerandomizing tests in route-regression analysis of avian population trends. pp. 63-70. in J. R. Sauer and S. Droege, editors, Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and Wildlife Service, Washington D.C. Biological Report 90(1), 166 pp.

Fisher, R. A. 1935. The design of experiments. Oliver and Boyd, Edinburgh-London (1st ed. 1935; 7th ed. 1960).

Friedland, K. D. 1993. History of salmon fisheries and management in the North Atlantic. Ninth ICES Dialogue Meeting, Edinburgh, Scotland. International Council for the Exploration of the Sea. Copenhagen, Denmark.

Friedland, K. D. and D. G. Reddin. 1993. Marine survival of Atlantic salmon from indices of post smolt growth and sea temperature. Fourth International Atlantic Salmon Symposium, St. Andrews, Canada. (in press).

Gasser, T. and H.-G. Muller. 1979. Kernel estimation of regression functions. pp. 23-68 in T. Gasser and M. Rosenblatt (eds.) Smoothing techniques for curve estimation. Springer-Verlag. New York.

Geissler, P. H. 1984. Estimation of animal population trends and annual indices from a survey of call counts or other indications. Proc.Amer. Statist. Assoc., Sect. Surv. Res. Methods 1984:472-477.

Geissler, P. H. and B. R. Noon. 1981. Estimates of avian population trends from the North American Breeding Bird Survey. Pages 42-51 in C. J. Ralph and J. M. Scott, editors. Estimating the numbers of terrestrial birds. Stud. Avian Biol. 6.

Geissler, P. H. and J. R. Sauer. 1990. Topics in route-regression analysis. pp. 54-57. in J. R. Sauer and S. Droege, editors, Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and Wildlife Service, Washington D.C. Biological Report90(1), 166 pp.

Hastie, T. and R. Tibshirani. 1990. Generalized additive models. Chapman and Hall, London.

James, F. C., C. E. McCulloch, and L. E. Wolfe. 1990. Methodological issues in the estimation of trends in bird populations with an example: the pine warbler. pp. 84-97. in J. R. Sauer and S. Droege, editors, Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and Wildlife Service, Washington D.C. Biological Report 90(1), 166 pp.

Jensen, A.L. 1976. Time series analysis and forecasting of Atlantic menhaden catch. Chesapeake Science 17:305-307.

Hippel, K. W. and A. I. McLeod. 1989. Intervention analysis in environmental engineering. Environmental Monitoring and Assessment 12:185-201.

Lehmann, E. L. 1975. Nonparametrics: Statistical methods based on ranks. Holden-Day, Inc. San Francisco, CA.

Manly, B. F. J. 1991. Randomization and Monte Carlo methods in Biology. Chapman and Hall Publ., London.

Mood, A. M., F. A. Graybill, and D. C. Boes. 1974. Introduction to the theory of statistics. (3rd edition) McGraw-Hill. New York.

Nelson, C. R. 1973. Applied time series analysis for managerial forecasting. Holden-Day, Inc., San Francisco, CA, USA

Neter, J., W. Wasserman, and M. H. Kutner. 1990. Applied linear statistical models: Regression, analysis of variance, and experimental design. 3rd edition. Irwin, Inc., Homewood, IL, USA

Pennington, M. 1985. Estimating the relative abundance of fish from a series of trawl surveys. Biometrics 41:197-202.

Piegorsch, W. W. 1990. Maximum likelihood estimation for the negative binomial dispersion parameter. Biometrics 46:863-867.

Raz, J. 1989. Analysis of repeated measurements using nonparametric smoothers and randomization tests. Biometrics 45:851-871.

Raz, J. and G. Fein. 1992. Testing for heterogeneity of evoked potential signals using an approximation to an exact permutation test. Biometrics 48:1069-1080.

Robbins,C. S., D. Bystrak, and P. H. Geissler. 1986. The breeding bird survey: its first fifteen years, 1965-1979. U. S. Fish and Wildlife Service, Resource Publication 157. 196 pp.

Rosenbaum, P. R. 1988. Permutation tests for matched pairs with adjustments for covariates. Journal of the Royal Statistical Society Series C 37:401-411.

Saila, S. B., M. Wigbout, and R. J. Lermit. 1980. Comparison of some time series models for the analysis of fisheries data. J. Cons. int. Explor. Mer 39:44-52.

Sauer, J. R. and S. Droege. Editors. 1990. Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and Wildlife Service, Washington D.C. Biological Report 90(1), 166 pp.

Silverman, B. W. 1985. Some aspects of the spline smoothing approach to nonparametric regression curve fitting. Journal of the Royal Statistical Society, Series B 47:1-52.

Soms, A. P. 1977. An algorithm for the discrete Fisher's permutation test. Journal of the American Statistical Association 72:662-664.

Taub, S. R. 1990. Smoothed scatterplot analysis of long-term Breeding Bird Census data. pp. 80-83 <u>in</u> J. R. Sauer and S. Droege, editors, Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and Wildlife Service, Washington D.C. Biological Report90(1), 166 pp.

Titus, K., M. R. Fuller, and D. Jacobs. 1990. Detecting trends in hawk migration count data. pp. 105-113. <u>in</u> J. R. Sauer and S. Droege, editors, Survey designs and statistical methods for the estimation of avian population trends. U. S. Fish and

Wildlife Service, Washington D.C. Biological Report90(1), 166 pp.

Ulanowicz, R. E., W. C. Caplins, and E. A. Dunnington. 1980. The forecasting of oyster harvest in central Chesapeake Bay. Estuarine and Coastal Marine Science 11:101-106.

Wilkinson, L. 1990a. SYGRAPH: The System for Graphics. SYSTAT, Inc., Evanston, IL.

Wilkinson, L. 1990b. SYSTAT: The System for Statistics. SYSTAT, Inc., Evanston, IL.

Table 1. Input data for route regression analysis. Counts of small salmon for various regions of Atlantic Canada. Missing or partial counts are denoted as -999. Symbols refer to Figure 1.

Scotia-Fundy Region	St John (□)	LaHave (Δ)	Liscomb (O)	
1984	7353	384	48	
1985	5331	638	87	
1986	6347	584	117	
1987	5097	532	88	
1988	8062	380	76	
1989	8417	511	75	
1990	6486	596	44	
1991	5415	236	38	
1992	5729	215	27	
Gulf-Mainland	Margaree(□)	Miramichi(Δ)	Restigouche (O)	
1984	400	29700	10900	
1985	600	60800	700	
1986	800	117500	10700	
1987	1500	84800	10000	
1988	2200	121900	13500	
1989	800	75200	6700	
1990	1000	83400	13650	
1991	1900	60900	7850	
1992	1000	152700	14800	
West Coast Newfoundland	Torrent (□)	Western Arm Brook (Δ)	Humber (O)	
1984	1805	117	-999	
1985	1553	162	-999	
1986	2815	252	-999	
1987	2505	378	12300	
1988	2065	102	16200	
1989	1339	414	4900	
1990	2296	124	12200	
1991	1415	233	5700	
1992	2347	480	22300	
South Coast Newfoundland	Conne(*)	Northeast Trepassey(□)	Biscay Bay (Δ)	Grand (O)
1984	-999	89	2430	-999
1985	-999	124	-999	-999
1986	7515	158	2516	211
1987	9687	91	-999	-999
1988	7118	97	1695	149
1989	4469	62	-999	175
1990	4321	71	1657	208
1991	2086	99	394	-999
1992	1973	49	-999	101

Quebec	Mitis(*)	Madeleine(□)	Matane(Δ)	Trinite (○)
1984	239	74	876	1663
1985	181	156	762	1008
1986	636	359	2364	1364
1987	225	406	1018	1115
1988	477	499	692	1324
1989	338	482	1208	1744
1990	528	452	1270	1637
1991	329	461	1586	1306
1992	697	509	1877	449
East Coast Newfoundland	Placentia Bay (*)	Terra Nova(□)	Middle Brook(Δ)	Gander (○).
1984	419	1233	1379	1081
1985	384	1557	904	1663
1986	725	1051	1036	1064
1987	-999	974	914	-999
1988	543	1737	772	1562
1989	706	1138	496	596
1990	551	1149	745	-999
1991	353	873	562	245
1992	921	1443	1182	1168

Table 2. Input data for Ratio Test: (A) counts of small-sized salmon at counting fences of Newfoundland. (B)counts of large-sized salmon at counting fences of Newfoundland.

(A)

Year	Humber	Rocky	Terra Nova	Middle Brook	Biscay Bay	Northeast River	Conne
1987	12,300	80	1,400	1,100	1,400	350	10,200
1988	16,200	300	2,100	1,300	1,800	640	7,600
1989	4,900	200	1,400	600	1,000	810	5,000
1990	12,200	400	1,500	1,100	1,700	700	5,400
1991	5,700	200	1,100	800	400	370	2,400
1992	22,300	300	1,800	1,600	1,300	960	2,500

(B)

Year	Humber	Rocky[1]	Terra Nova	Middle Brook	Biscay Bay	Northeast River	Conne
1987	900		60	19	110	16	500
1988	1,100		210	14	60	11	40
1989	300		140	19	100	15	30
1990	900		140	13	70	25	40
1991	400		110	14	40	8	100
1992	3,700		270	43	50	46	200

[1] Only partial counts were available in 1990-1992. River was not used for ratio test.

Table 3. Summary of route regression analyses for log transformed counts of returning small salmon in Atlantic Canada. The sampling distribution of the composite trend estimate was based on 5000 randomizations for each region. (A) Summary of parameters used to compute critical value B_0 for composite slope (Eq. 3). (B) Percentiles for approximate sampling distribution.

(A) Scotia Fundy Region

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Liscomb	-0.1145009	0.0024411	60.88	24939.98
2	LaHave	-0.0883224	0.0019720	424.68	215352.95
3	StJohn	-0.0067719	0.0006439	6372.11	9896871.00

Gulf-Mainland (counts expressed in thousands)

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Restigouc	0.0270571	0.0014766	10.42	7054.19
2	Miramichi	0.0954229	0.0031503	79.83	25340.88
3	Margaree	0.0889984	0.0025451	1.25	491.62

West Coast Newfoundland

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Humber	0.0215249	0.0249468	10716.10	429558.56
2	W_Arm_Brk	0.0900584	0.0053339	217.05	40691.97
3	Torrent	-0.0043844	0.0013388	1955.02	1460269.75

South Coast Newfoundland

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Grand	-0.0936675	0.0031933	163.39	51165.91
2	Biscay	-0.2072258	0.0091449	1466.06	160314.31
3	NETrepass	-0.0838613	0.0013541	88.61	65440.37
4	Conne	-0.2707694	0.0019954	4563.21	2286920.75

Quebec

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Trinite	-0.0607875	0.0027492	1212.44	441016.25
2	Matane	0.0695760	0.0025840	1198.09	463655.63
3	Madeleine	0.1930435	0.0031280	327.44	104682.38
4	Mitis	0.1017400	0.0029356	367.28	125112.27

East Coast Newfoundland

Series	Label	Slope	V(Slope)	Z_hat	Weight
1	Gander	-0.1124922	0.0072054	908.47	126082.27
2	Middle	-0.0551951	0.0016563	846.96	511345.00
3	TerraNova	-0.0128799	0.0009416	1211.75	1286929.13
4	Placentia	0.0442213	0.0019485	547.21	280829.69

Table 3. (cont.)
(B)

Percentile of (B_o)	Scotia-Fundy	Gulf-Mainland	West Coast Newfoundland	South Coast Newfoundland	Quebec	East Coast Newfoundland
.01	-.0520	-.1092	-.1468	-.1735	-.0838	-.0565
.025	-.0455	-.0943	-.1131	-.1525	-.0742	-.0500
.05	-.0398	-.0785	-.0910	-.1292	-.0622	-.0431
.10	-.0316	-.0635	-.0680	-.1027	-.0492	-.0339
.25	-.0168	-.0360	-.0350	-.0556	-.0263	-.0185
.50	-.0001	.0000	.0002	-.0009	.0001	-.0001
.75	.0164	.0353	.0345	.0525	.0267	.0181
.90	.0316	.0642	.0687	.1045	.0502	.0343
.95	.0400	.0789	.0916	.1318	.0621	.0422
.975	.0455	.0943	.1133	.1520	.0727	.0509
.99	.0511	.1120	.1430	.1759	.0824	.0591
Critical Value (B_o)	.0087693	.0806624	.00337138	-0.258491	.03383813	-0.0211154
Significance Level of (B_o)	0.6344	0.0458	0.476	1.0000	0.1982	0.7840

Table 4. Summary of ratio tests results for counts of salmon in Newfoundland. Sampling distribution was approximated using 2000 randomizations of the input data from Table 2. Mean count for 1992 was compared to the 1987-1991 mean.

Statistic	Small Salmon	Large Salmon
Observed Ratio $\mathbf{R_o}$	1.469661	3.914426
Significance Level for $\mathbf{R_o}$	0.130	.0325
Minimum Simulated Value	.3965407	.2470324
Percentiles of $\mathbf{R_o}$		
.01	.4477793	.2820540
.025	.4821862	.2974519
.05	.5071580	.3221608
.1	.5514103	.3570259
.25	.7596768	.4680709
.5	.9836497	.7446435
.75	1.248154	.9798903
.9	1.528300	3.499047
.95	1.657325	3.664136
.975	1.810683	4.081066
.99	1.919264	4.200263
Maximum Value	2.016062	4.482992

FIGURE CAPTIONS

Figure 1. LOWESS smoothed, log transformed ($\log_e [Y_t+0.23]$) count data for small salmon in 21 rivers of Atlantic Canada, 1984-1992. Tension parameter was set to 0.8. **(A)** Scotia-Fundy Region: St John (□), LaHave (▵), Liscomb (○); **(B)** Gulf-Mainland: Margaree(□), Miramichi(▵), Restigouche (○); **(C)** West Coast Newfoundland: Torrent (□), Western Arm Brook (▵), Humber (○); **(D)** South Coast Newfoundland: Conne(★), Northeast Trepassey(□), Biscay Bay (▵) and Grand (○); **(E)** Quebec: Mitis(★), Madeleine(□), Matane(▵), Trinite(○); and **(F)** East Coast Newfoundland: Placentia Bay (★), Terra Nova(□), Middle Brook(▵), Gander (○).

Figure 2. Effect of increase in the number of sites from 1 to 11 on the ability to detect changes in the mean abundance level of fish for true underlying changes of (A) $\delta=1.1$, (B) $\delta=1.25$, (C) $\delta=1.1^{-1}$, and (D) $\delta=1.25^{-1}$. The mean abundance level for the 8-yr baseline period was $\mu=500$. Power was approximated with 500 random data sets for each ratio and number of series combination. The sampling distribution for each random data set was approximated with 1000 re-randomizations of the data. Each point represents the fraction of cases in which the significance level of the ratio test was less than the Type I error level [$\alpha=0.20$ (□); $\alpha=0.05$ (○); $\alpha=0.01$ (▵)]. Points were connected by spline fit.

Figure 3. Estimated power to detect true change in ratio of means for a hypothetical time series at 5 simulated sites with underlying means of 1250, 625, 500, 300, 50. An eight year baseline and 2-year treatment period was assumed. Power was approximated with 500 random data sets for each ratio. The sampling distribution for each random data set was approximated with 1000 re-randomizations of the data. Each point represents the fraction of cases in which the significance level of the ratio test was less than the Type I error level [$\alpha=0.20$ (□); $\alpha=0.05$ (○); $\alpha=0.01$ (▵)]. Points were connected by spline fit.

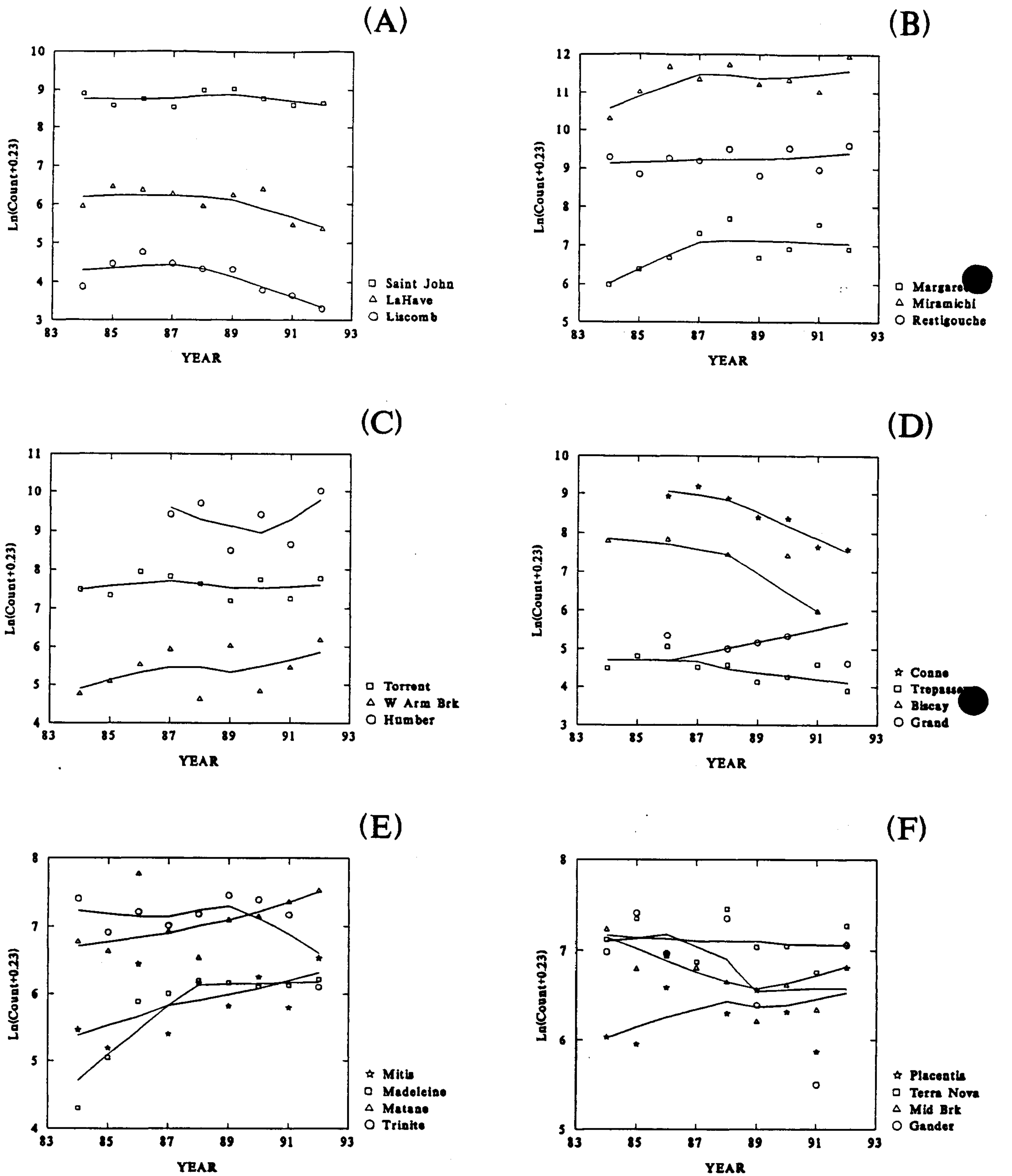

(A)
Ln(Count+0.23)
YEAR
Saint John
LaHave
Liscomb
(B)
Ln(Count+0.23)
YEAR
Margare
Miramichi
Restigouche
(C)
Ln(Count+0.23)
YEAR
Torrent
W Arm Brk
Humber
(D)
Ln(Count+0.23)
YEAR
Conne
Trepass
Biscay
Grand
(E)
Ln(Count+0.23)
YEAR
Mitis
Madeleine
Matane
Trinite
(F)
Ln(Count+0.23)
YEAR
Placentia
Terra Nova
Mid Brk
Gander

FIGURE 1

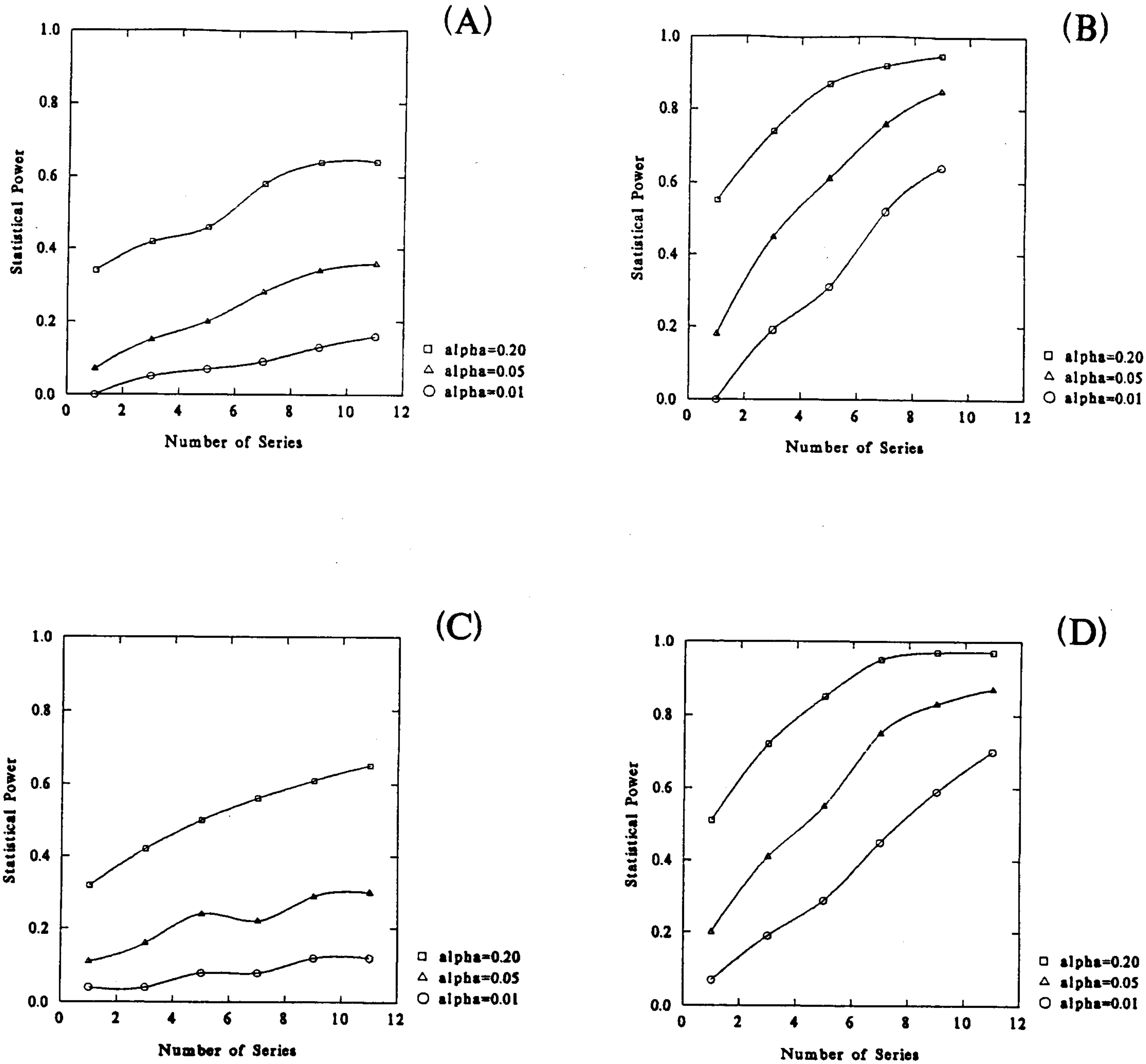
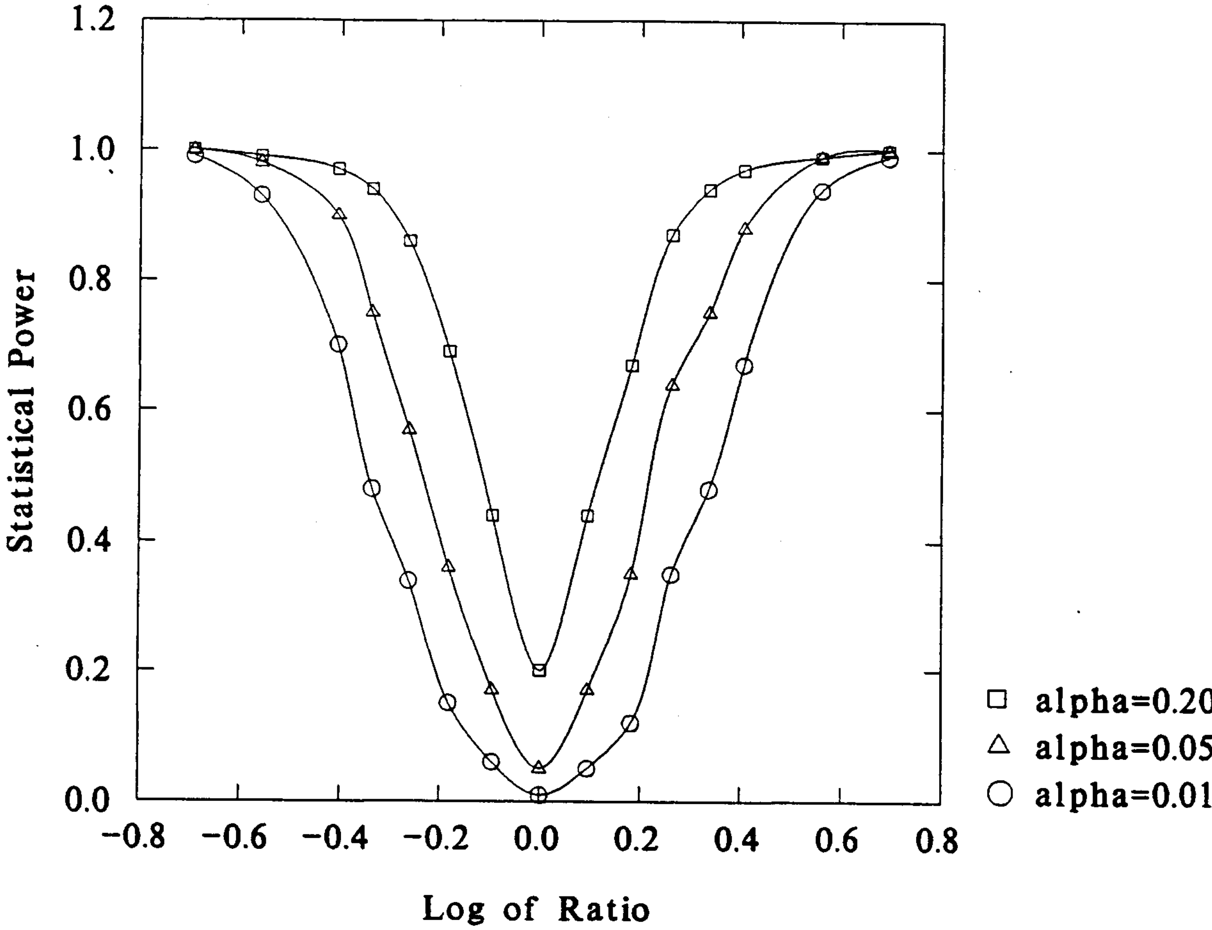

(A)
(B)
(C)
(D)
Statistical Power
Number of Series
alpha=0.20
alpha=0.05
alpha=0.01
0.0
0.2
0.4
0.6
0.8
1.0
0
2
4
6
8
10
12

FIGURE 2.

FIG. 3



1.2
1.0
0.8
0.6
0.4
0.2
0.0
Statistical Power
−0.8 −0.6 −0.4 −0.2 0.0 0.2 0.4 0.6 0.8
Log of Ratio
alpha=0.20
alpha=0.05
alpha=0.01