Fisheries and Oceans / Pêches et Océans

Canadian Stock Assessment Secretariat
Research Document 98/147

Secrétariat canadien pour l'évaluation des stocks
Document de recherche 98/147

The analysis of 1997 small salmon returns to Newfoundland rivers using distributional testing.

by

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ISSN 1480-4883
Ottawa, 1998
Canada

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Abstract

Data available of small salmon returns to Newfoundland rivers were used to determine the appropriate statistical distribution for describing those same returns. Only those data series which were judged to be statistically adequate random samples were used in distributional testing procedures. Anderson-Darling tests were used to test the acceptability of the Normal, Lognormal and Weibull distributional models as descriptions of small salmon returns. P-values, allowing selection between the candidate models were also computed and reported. Distributional models selected as the best descriptors of the returns data were then parameterized using available historical data and used to compute the probabilities of observing returns as low as those reported for 1997. Computed probabilities indicate some rivers experienced abnormally low returns in 1997 (N.E. Trepassey and Salmon Brook), while others did not (Rocky and Exploits). Although data were not adjusted for losses to the commercial fishery priory to 1992, conclusions reached here apply to observations about trends in the actual size of potential small salmon spawning stocks. On balance there appears to be little evidence of a large scale synchronous decline in small salmon returns to Newfoundland rivers.

Résumé

Les données sur les remontées de petits saumons dans les rivières de Terre-Neuve ont été utilisées pour déterminer la distribution statistique décrivant le mieux les remontées. Seules les séries de données jugées correspondant à des échantillons aléatoires statistiquement valables ont été utilisées pour tester les distributions. Les tests de Anderson-Darling ont été appliqués aux modèles de distribution normale, lognormale ou de Weibull pour la description des remontées de petits saumons. Les valeurs de P, permettant de choisir entre les modèles, ont été calculées et indiquées. Les modèles décrivant le mieux les données sur les remontées ont ensuite été paramétrés à l'aide des données historiques utilisées pour le calcul de la probabilité d'observer des remontées aussi faibles que celles signalées pour 1997. Les probabilités calculées indiquent des remontées anormalement faibles dans certaines rivières en 1997 (N.E Trepassey et Salmon Brook), mais non pour d'autres (Rocky et Exploits). Bien que les données n'aient pas été corrigées pour les pertes attribuables à la pêche commerciale avant 1992, les conclusions tirées s'appliquent quand même aux observations sur les tendances de l'effectif réel de stocks de petits saumons géniteurs. Il semble, de façon générale, qu'il n'y ait pas eu de déclin synchrone des remontées de petits saumons dans les rivières de Terre-Neuve.

Introduction

Questions regarding adult salmon returns in 1997 to Newfoundland rivers have been raised as a result of the apparent low abundance of salmon throughout much of the region. Concerns focus on the possibility that observed returns were anomalously low and that stocks may, as a consequence, be in danger. One means of assessing the question is to determine the appropriate statistical distribution to describe available returns data. In addition to describing the range of probable returns, distributional models allow formal expectations concerning the likelihood of observing any given level of returns to be formed. Finally, distributional models provide resource managers with a convenient means of visualizing likely return ranges and their associated relative probabilities.

Methods

1. Data

The data sets used to determine the form of the statistical distribution best describing salmon returns are provided in Appendix 1. These have been updated and expanded from the data sets summarized in Dempson et al. (1997). The data details estimates of total returns of small Atlantic salmon (individuals < 63 c m in fork length) and, where required, accounts for in-river losses to recreational fisheries that occurred downstream of fish counting facilities. No attempt has been made to adjust the return data for losses to marine exploitation prior to 1992 when the commercial fishery for Atlantic salmon was in existence.

As distributional testing procedures require data that are uncorrelated (independent), the obtained data sets were first tested for serial correlation before goodness-of-fit tests were used to determine which distribution best described the data. Accordingly, a two stage testing procedure was used. In the first stage, each data series was tested for serial correlation using randomization test procedures. In the second stage, those series found to contain no significant serial correlation were further tested for compatibility with a variety of distributional assumptions to determine which, if any, distributional model best described the available returns data. The distributional models were then used to determine the probability of observing returns as low, or lower, as those recorded for 1997.

2. Randomization tests

The null hypothesis for goodness-of-fit tests require that the data being tested represent a random sample from an hypothesized distribution (Stephens, 1986). Accordingly, before goodness-of-fit tests may be appropriately used as a means of establishing whether the available data represent a random sample from a given distribution, the randomness assumption must be confirmed. In time series data this can be accomplished by assessing the significance of any observed serial correlation within the data.

Serial correlation among a time-ordered sequence of random variables indicates that the random variables at different time periods are correlated. In a non-random time series, observations that are a distance k apart will show a relationship, the strength of which can be measured using sample autocorrelation coefficients. When the observations are equally spaced in time the k^{th} sample autocorrelation coefficient is estimated by:

$$r_k = \frac{\sum_{i=1}^{n-k} (X_i - \bar{X})(X_{i+k} - \bar{X}) / (n-k)}{\sum_{i=1}^{n} (X_i - \bar{X})^2 / n} \quad (1)$$

where $X_1, \ldots, X_n$ are the data values in the series with mean $\bar{X}$.

The significance of each of the r_k values can be tested using randomization tests (Manly 1992). The tests are applied by calculating the observed r_k (k = 1, ..., 10 years) values from the returns data using equation (1).This requires that candidate data sets have at least 10 observations. Accordingly, data sets for the Gander and Campbellton rivers were not suitable for the suggested testing procedure. However, sufficient data for a tributary of the Gander River, Salmon Brook were available. Over the period of joint monitoring, 1989-1997, returns to Salmon Brook have been highly correlated with returns for the entire Gander River system (r = 0.907), suggesting that results for Salmon Brook will serve as adequate proxy for the entire system.

Data are used in the order of historical occurrence to compute initial r_k values. Data are then randomly permuted and the resulting r_k (k = 1, ..., 10) values for the new data series are computed. The permutation and re-calculation of the r_k values are completed a large number of times and the empirical distributions of the r_k values at lag *k* constructed. The resulting empirical distributions provide convenient descriptions of the probabilities associated with observing given r_k values and may be used for drawing inferences about the acceptability of the null hypothesis. This is done by calculating the proportion of all values of r_k in the empirical distribution greater than or equal to the value of r_k at lag <u>k</u> computed for the original data series. Since the proportion of such values is an estimate of the probability of observing the value of r_k it is also the significance attached to the computed r_k in the original data series. If the proportion is less than or equal to a chosen level of significance, α, then the computed r_k at lag *k* for the original data series is significant and the hypothesis of no significant serial correlation is rejected.

A test that involves sampling from a randomization distribution is exact in the sense that using a $100\alpha\%$ level of significance has a probability of α, or less, of giving a significant result when the null hypothesis is true (Manly, 1992). While an infinitely large number of randomizations is not necessary, there is a minimum number which must be completed. The number completed should be sufficient to insure that the significance level estimated from the number of randomizations completed is close to the level that would be obtained from considering all possible permutations of the data.

The correspondence between the significance level yielded by the randomization testing procedure and that obtained by considering all possible permutations of the data can be computed by calculating the limits within which the significance level estimated from the randomization procedure will lie 99 percent of the time for a given significance level p from the full distribution using the approach given in Edgington (1987) as follows:

$$p = 2.58\sqrt{\frac{p(1-p)}{n}} \quad (2)$$

where n is the number of randomizations completed. Setting p = 0.01 and n = 5000 yields sampling limits of 0.006 and 0.014 within which the estimated significance level of the randomization procedure will fall. As this is close to the desired 0.01 significance level that would be obtained from the complete enumeration procedure, n was set at 5000 for the completion of the randomization tests reported below.

When a number of sample autocorrelation coefficients are tested for significance at the same time there is a probability of declaring at least one of them to be significant by chance alone. If K significance tests are conducted simultaneously, each with significance level α_j, then the probability of all K tests being correct simultaneously will be given by the Bonferroni inequality:

$$1 - \sum_{j=1}^{K} \alpha_j \tag{3}$$

whether or not the test statistics used are independent. Equation (3) thus states that if K serial autocorrelations are tested using the ($\alpha_j = \alpha/K$)% significance level for each test, then there is a probability of only $\alpha/100$ or less of declaring any of them significant by chance. Accordingly, in selecting the appropriate level of significance for the completion of each of the significance tests on the r_k values, due consideration must be given to the effect of the Bonferroni inequality on the implied level of significance for the randomization test as a whole.

3. Goodness-of-fit testing

Empirical distribution function (EDF) statistics are based on the empirical distribution function which is calculated as a step function from the sample data. EDF statistics are measures of the differences between the EDF and an hypothesized distribution function F(x) and are used in goodness-of-fit testing to assess the fit of the sample data to the hypothesized distribution.

Consider a random sample of size n, $X_1, X_2, \ldots X_n$. Let $X_{(1)} < X_{(2)} < \ldots < X_{(n)}$ be the order statistics for the sample. The EDF is denoted as $F_n(x)$ and is defined as:

$$\begin{aligned} F_n(x) &= 0 & x &< X_{(1)} \\ F_n(x) &= \frac{i}{n} & X_{(i)} \le x &< X_{(i+1)} \\ F_n(x) &= 1 & X_{(n)} &\le x \end{aligned} \tag{4}$$

For any X, $F_n(x)$ records the proportion of observations in the sample data less than or equal to X. On the otherhand, F(x) is the probability of an observation being less than or equal to X for the hypothesized distribution. If $F_n(x)$ can be expected to approximate F(x), then any statistic measuring the difference between $F_n(x)$ and F(x) will provide a measure of the goodness-of-fit of $F_n(x)$ to F(x).

The EDF statistic employed here for goodness-of-fit testing is the Anderson-Darling statistic, A^2. It concentrates on the vertical differences between $F_n(x)$ and F(x) over the entire range of the considered data and is drawn from the Cramer-von Mises family of statistics defined by Q:

$$Q = n \int_{-\infty}^{\infty} [\, F_n(x) - F(x) \,]^2 \, \psi(x) \, dF(x) \tag{5}$$

where $\psi(x)$ is a function that weights the squared differences between the empirical and hypothesized distribution functions using the expression [F(x)/(1-F(x))].

Stephens (1986) reports that power studies for normality and exponentiality tests indicate that A^2 is the recommended omnibus test statistic for EDF tests in which the required distributional parameters for F(x) are estimated from the sample data. In the cases discussed below the parameters of the hypothesized recruitment distributions were estimated directly from the data with appropriate maximum likelihood (MLE) techniques. Furthermore, the data were tested directly for normality or exponentiality, or transformed such that they could be tested for normality (e.g. lognormal models) or exponentiality (e.g. Weibull models). See, for example, Law and Kelton (1991) for methodological details. Hence, the choice of A^2 as the test statistic is appropriate. Finally, following Stephens (1986) the A^2 values were used only to indicate the appropriateness of the hypothesized distribution function as a model of the true recruitment distribution. Since the distribution of A^2 will vary with F(x), the value of A^2 itself will not indicate which of a series of hypothesized distribution functions best fits the data. Instead, the p-value attached to A^2 must be used as an indicator of the true population from which the data were sampled, with a larger p-value (measured from the upper-tail) indicating a better fit.

This suggests a two phase testing procedure for data sets containing 10, or more, observations. In the first phase tests are used to establish the candidacy of a particular distributional model as the best description of the data by determining the statistical adequacy of an hypothesized distribution as a description of the data. Because the distribution of A^2 will vary with F(x), a second phase of testing is required in which the p-values are computed and used to arbitrate between candidate models as a means of selecting which, if any, of the considered distributional models "best" describes the data.

The randomization tests were completed with the aid of the testing subroutines given in Manly (1992). The test statistic A^2 was computed using the Davis and Stephens (1989) algorithm AS 248. The algorithm computes A^2 and appropriately modifies it such that only one line of significance points is required to judge the acceptability of the null hypothesis. At the 5 percent level of significance non-serially correlated data sets were accepted as adequate descriptions of the normal, lognormal or Weibull distributions if the computed A^2 statistics were less than 0.752, 0.752 and 1,321 respectively. Approximate p-values were also calculated using the formulae from Stephens (1986). The values are most accurate in the upper-tail and provide a convenient means of distinguishing between candidate models in terms of which provides the "best" fit to the data. Higher p-values indicate a better fit and the distributional model having the highest p-value was selected as the "best" description of the returns data.

Results and Discussion

1. <u>Randomization testing results</u>

Table 1 gives the results of the randomization tests. For each of the tested data sets the largest r_k value, the lag (k) at which it occurred and the smallest p-value (% terms) associated with an observed r_k value are given. The critical value for determining randomness was determined by applying the Bonferroni inequality to the desired overall level of significance, set here as 0.10, using equation (3). Thus, probability values $\leq$ 1.00% are indicative of non-randomness in the data set. Such data sets are not suitable for distributional testing and were excluded from further analysis. Data for the Terra Nova, Conne, Lomond and Torrent rivers were excluded from distributional testing on this basis.

2. <u>Distributional testing results</u>

Table 2 gives the results of the distributional testing for each of the data sets found to be random. Three distributional models were tested for: normal, lognormal and Weibull. The table reports the p-values associated with the Anderson-Darling test statistic only for those distributional models found to be consistent with the data at the 0.05 level of significance. That is, each model for which a p-value is reported is consistent with the data at the 0.05 level of significance and should be considered as a candidate for the "best' model. The "best" model, based on the p-value results, is underlined in each case. Of the nine tested sets, four were found to be best described by the lognormal model, four by the Weibull model and the evidence for the applicability of either model to the data for Western Arm Brook was weak.

3. <u>Returns distribution parameter estimates</u>

Table 3 reports the distributional parameter estimates for each of the selected models. For the lognormal models the parameters μ and σ, corresponding to the scale and shape parameters are reported. The shape and scale parameters of the lognormal distribution were estimated by their respective MLE estimators as given in Law and Kelton (1991). For the Weibull distribution the parameters α and β, corresponding to the scale and shape parameters are reported. The scale and the shape parameters of the Weibull distribution were estimated directly from the data following the MLE procedure outlined in Thoman et al. (1969). Finally, based on the estimated parameters, return distributions for each of the considered rivers are plotted in Fig.1 to Fig. 9 (Appendix 2) along with the associated current arithmetic mean return.

4. <u>River-specific return probabilities</u>

Table 4 uses the distributional models defined by the parameter estimates given in Table 3 to compute the probability of observing returns as low, or lower, than the value recorded in 1997. See, for example, Hogg and Craig (1978) or DeGroot (1986) for a description of the appropriate methods. This involves computing the probabilities defined by the lower tail of each of the distributional models. One minus the value given in column 2 of the table will, therefore, define the probability of observing returns larger than those observed in 1997. For convenience, these latter values have been included in Table 4. Finally, because over-estimates of the actual returns have the greatest consequences for management policy (e.g. over-estimating actual returns leads to greater likelihood of management decisions resulting in damage to stocks than does under-estimating returns), probabilities associated with observing returns low, or lower, than 90% of actual returns are also included in Table 4.

Based on the computed results, there is strong evidence for the occurrence of low returns in the N.E. Trepassey and Salmon Brook rivers. Middle Brook returns fall in the lower third of the distribution, while returns to the Rocky river are amongst the highest likely to be seen. All other return values fall in the mid-range of expected return values and cannot be construed to be either particularly low or high. Although on balance there appears to be little evidence of a large scale, synchronous decline in small salmon returns to Newfoundland rivers, the analyses completed here do not attempt to adjust, or correct , return information to account for commercially harvested salmon in the years prior to 1992. Commercial fishing will have had the effect of lowering river measured returns in the years in which the fishery was in operation and may, as a result, have shifted distributions on estimated river returns to the left. In addition to changing the estimated location of the returns distribution, corrections for commercial harvest are likely to influence estimates of the distributional shape parameter. The consequent effect of adjustments to the returns data on conclusions for the prevalence of low returns in Newfoundland rivers in 1997, therefore, are not easily predicted. In cases where salmon return data could be converted to total stock size by using, for example, the river-specific marine exploitation data presented in Dempson et al. (1997), conclusions concerning the probability of observing returns as low, or lower, that those seen in 1997 on a river by river basis might change. Nevertheless from a management perspective, conclusions concerning the relative size of the potential small salmon spawning stock net of fishing mortality, the probability of observing a stock of that size and its probable net contribution to the next generation, will not be affected by adjustments aimed at estimating the hypothetical, rather than the actual, potential small salmon spawning stock size.

Acknowledgements

J. B. Dempson and G. Power are to be thanked for encouraging the completion of the analysis. J. B. Dempson kindly provided the data provided in Appendix 1 that allowed the work to be completed in the first place.

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Table 1. Randomization testing results for selected Newfoundland rivers. The value r_k defines the largest sample autocorrelation coefficient computed for the available small salmon returns data. Percent p-values < 1.00 indicate non-randomness in the returns data.

River	Years	Largest r_k	Lag (k)	Percent p-value
Northeast Coast				
Exploits	1984-96	0.420	1	4.34
Salmon Brook	1980-97	-0.292	9	6.22
Middle Brook	1978-97	0.348	1	6.48
Terra Nova	1978-97	0.456	1	2.42
South Coast				
Biscay Bay	1983-96	0.584	2	0.88
N.E. Trepassey	1984-97	0.301	1	20.12
Rocky	1987-97	0.315	2	2.10
N. E. Placentia	1978-97	0.348	3	7.50
Conne	1986-97	0.694	1	0.12
West Coast				
Humber	1974-97	0.149	1	44.34
Lomond	1971-97	0.490	1	0.54
Torrent	1971-97	0.765	1	0.02
W. Arm Brook	1971-97	-0.332	1	3.42

Table 2. Distributional testing results for selected Newfoundland rivers based on historical data. The p-values for the distributional tests indicate the probability that the data conforms to a given distributional model. The "best" distributional models are those with the p-values underlined.

River	Normal	Lognormal	Weibull
Northeast Coast			
Exploits	0.110	<u>0.683</u>	0.571
Salmon Brook	0.421	0.109	<u>0.760</u>
Middle Brook	0.575	0.425	<u>0.798</u>
Terra Nova	0.084	<u>0.677</u>	0.352
South Coast			
N.E. Trepassey	0.341	<u>0.774</u>	0.614
Rocky	0.854	0.317	<u>0.884</u>
N. E. Placentia	0.585	0.693	<u>0.925</u>
West Coast			
Humber	0.117	<u>0.735</u>	0.598
W. Arm Brook	0.001	0.059	0.057

Table 3. Parameter estimates for distributions and distribution type describing small salmon returns to selected Newfoundland rivers.

River	Shape	Scale	Model Type
Northeast Coast			
Exploits	0.432	9.409	Lognormal
Salmon Brook	2.115	1231.783	Weibull
Middle Brook	3.254	1727.336	Weibull
Terra Nova	0.310	7.386	Lognormal
South Coast			
N.E. Trepassey	0.309	4.420	Lognormal
Rocky	2.835	310.354	Weibull
N. E. Placentia	2.520	732.723	Weibull
West Coast			
Humber	0.434	9.502	Lognormal
W. Arm Brook	0.455	6.308	Lognormal
	2.100	694.869	Weibull

Table 4. Probabilities of observing returns ≤ to those in 1997 or returns > to those in 1997 in selected Newfoundland rivers. Probabilities of observing returns ≤ to 90 % of those in 1997 are also given.

River	1997 Returns	Probability Returns < 1997 Returns	Probability Returns > 1997 Returns	Probability Returns < 90 % of 1997 Returns
Northeast Coast				
Exploits	15263	0.699	0.301	0.610
Salmon Brook	465	0.120	0.880	0.097
Middle Brook	1287	0.319	0.689	0.238
Terra Nova	1786	0.629	0.371	0.496
South Coast				
N.E. Trepassey	50	0.051	0.949	0.024
Rocky	435	0.926	0.074	0.855
N. E. Placentia	722	0.618	0.382	0.522
West Coast				
Humber	14004	0.504	0.496	0.444
W. Arm Brook				
Lognormal	509	0.433	0.567	0.345
Weibull	509	0.406	0.584	0.341

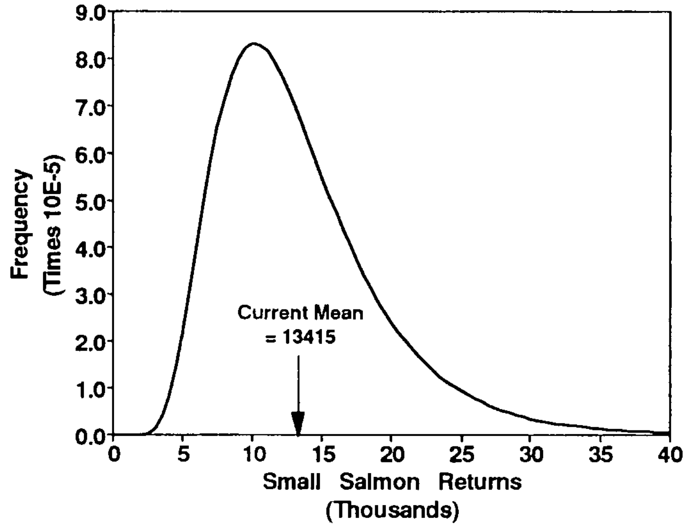

Figure 1. Small salmon returns distribution for the Exploits River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

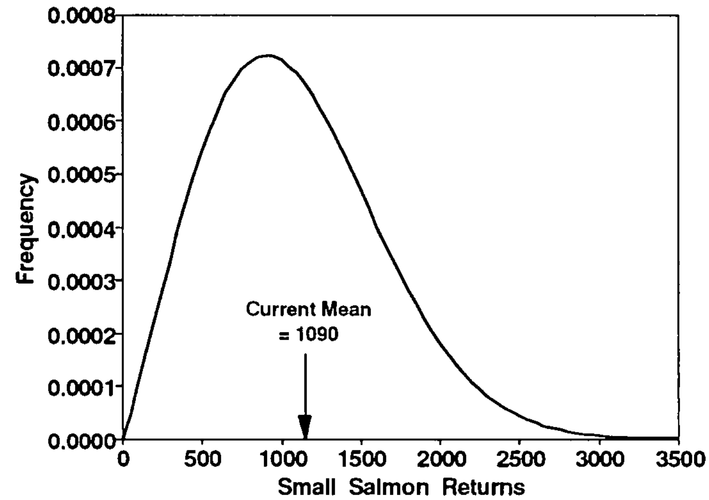

Figure 2. Small salmon returns distribution for Salmon Brook based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

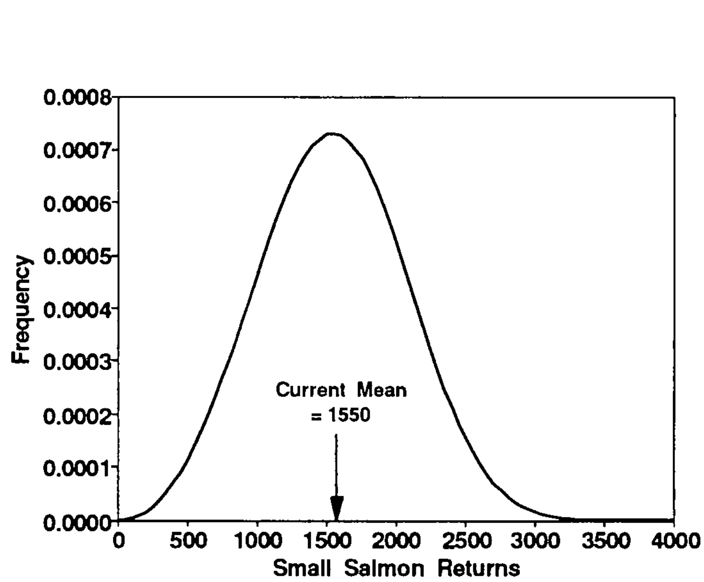

Figure 3. Small salmon returns distribution for Middle Brook based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

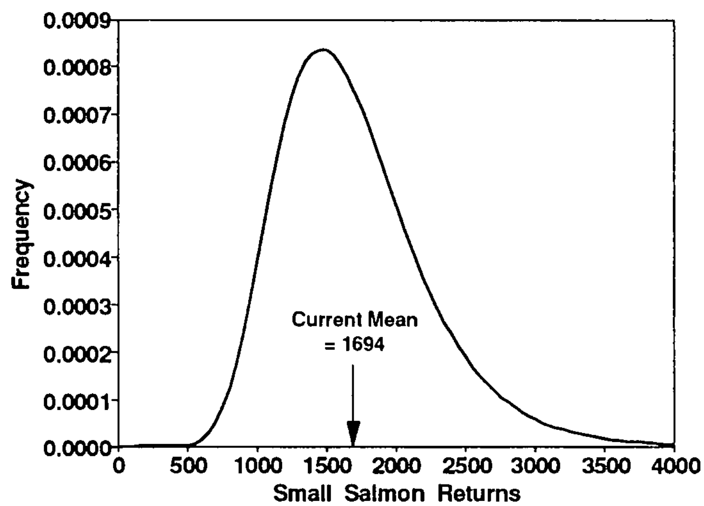

Figure 4. Small salmon returns distribution for the Terra Nova River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

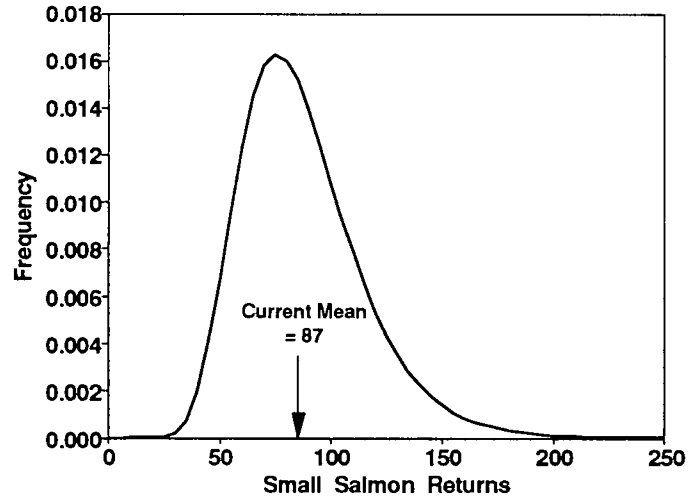

Figure 5. Small salmon returns distribution for the N. E. Trepassey River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

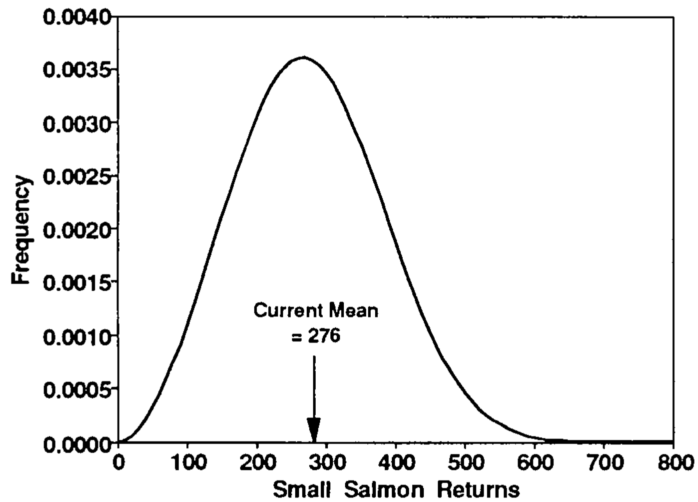

Figure 6. Small salmon returns distribution for the Rocky River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

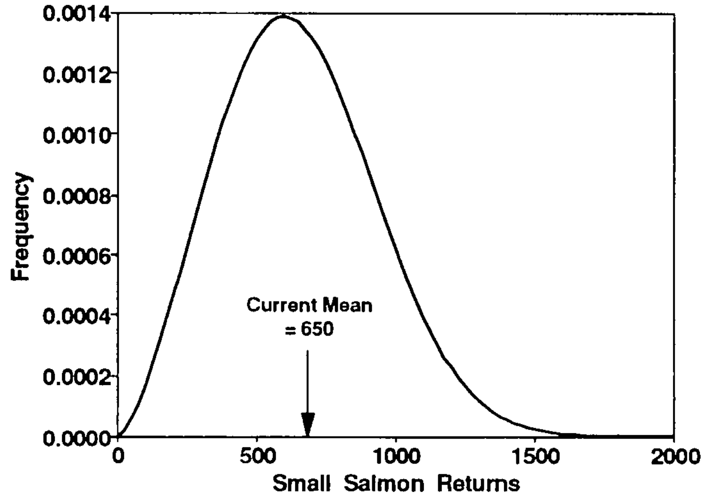

Figure 7. Small salmon returns distribution for the N. E. Placentia River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

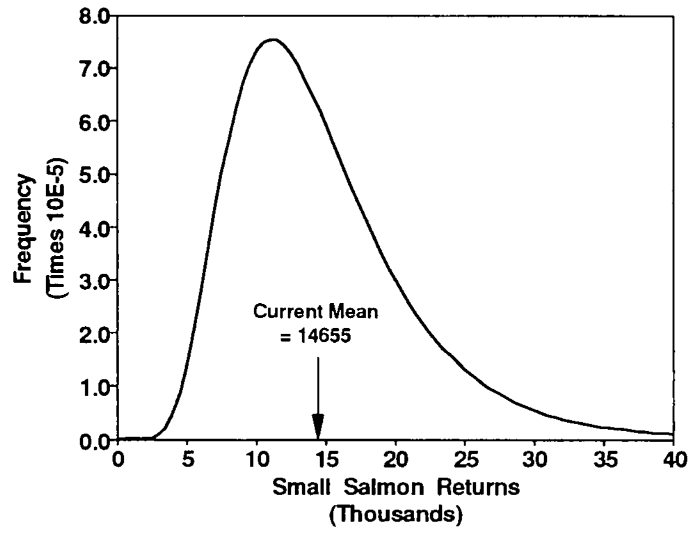

Figure 8. Small salmon returns distribution for the Humber River based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

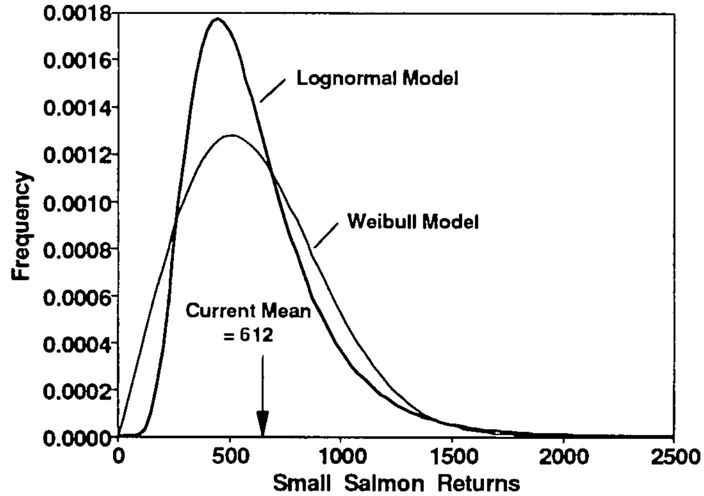

Figure 9. Small salmon returns distribution for Western Arm Brook based on the distributional parameter estimates given in Table 3. Parameters used to plot the returns distribution were estimated suing the data given in Appendix 1. Current mean is the rounded arithmetic mean of the data in Appendix 1.

Appendix 1. Total returns of small Atlantic salmon (fish < 63 cm) to various Newfoundland rivers. Where required, adjustments have been made to account for salmon harvested in recreational fisheries that occur below fish counting facilities. Data have not been corrected to account for marine exploitation in years prior to the closure of the Newfoundland commercial salmon fishery in 1992.

Small salmon

	Northeast Coast						South Coast					West Coast			
Year	Exploits	Salmon Bk.	Gander	Middle Bk.	Terra Nova	Campbellton	Biscay Bay*	Northeast Trepassey	Rocky	Northeast Placentia	Conne	Humber	Lomond	Torrent	Western Arm Bk.
1971													60	107	632
1972													283	86	406
1973													394	184	797
1974												10968	365	96	506
1975												24588	259	314	639
1976												20408	782	341	552
1977												8632	687	789	373
1978				1692	1174					495		10888	462	1002	315
1979				1371	880					544		13372	430	2049	1578
1980	13344	997		2113	1140					593		14048	594	792	465
1981	9672	2459		2848	1544					561		16528	617	2268	492
1982	9124	1425		1654	1233					184		17148	583	2299	467
1983	8259	978		1470	1492		2330			340		12440	471	2089	1141
1984	19028	1081		1675	1534		2430	89		459		11488	986	1805	235
1985	17555	1663		1283	2012		1926	124		519		9720	393	1623	467
1986	10343	1064		1547	1459		2688	158		879	8302	13824	725	3155	527
1987	9481	493		1053	1404		1393	91	80	350	10155	12296	652	2670	437
1988	9496	1562		1337	2114		1802	97	313	637	7627	16168	841	2388	422
1989	7577	596	7743	626	1377		1004	62	168	809	4968	4868	652	1512	455
1990	6995	345	7740	1070	1518		1670	71	401	699	5368	12216	777	2518	444
1991	5659	245	6745	763	1127		394	99	211	368	2411	5724	731	1591	233
1992	13504	1168	18179	1563	1780		1467	49	237	956	2523	17571	794	2832	480
1993	22150	1560	26205	2247	3050	4001	1117	79	292	980	2703	18477	816	4215	947
1994	17556	968	18273	1844	2035	2857	1600	99	158	710	1533	7995	1038	3827	954
1995	16149	1600	22266	1448	2638	3035	1151	80	385	774	3502	27898	1365	6168	823
1996	30316	946	23946	2112	2575	3208	1217	73	356	1420	4440	30445	982	7371	1230
1997	15263	465	10591	1287	1786	1975		50	435	722	3200	14866	1307	4034	509

* Biscay Bay fish counting fence was not operated in 1997