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In-season forecasting of North Coast coho salmon marine survival: a decision analytic method and retrospective analysis

Prévision en saison de la survie en mer du saumon coho des zones côtières nordiques par une méthode analytique d'aide à la décision et une analyse rétrospective

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Abstract

This paper develops an estimation algorithm that is intended to provide early warnings of poor marine survival conditions for Canadian North Coast coho stocks. The modelling approach attempts to partition weekly variation in observed coded-wire tagged (CWT) coho catches in boundary troll fisheries into components that depend upon total CWT coho smolts released, troll fishing effort, and marine survival rates. Uncertainty in marine survival rate forecasts is addressed via a Bayesian decision analytic framework, which accounts for overfishing risk. Statistical approaches, forecast accuracy, and forecast biases were tested using simulated data.

Retrospective marine survival forecasts compared favorably with actual marine survival estimates obtained from post-season catch and escapement estimates and with previous assessments that attempted to forecast marine survival. The algorithm provided accurate warnings of poor marine survival conditions in all years for which such warnings were required. One false warning was issued from 19 possible cases, or a 5% Type I error rate.

The marine survival forecasting procedure provides early warnings of poor marine survival up to 6 weeks in advance of the Canadian coho fishery opening. Therefore, it allows sufficient time for Canadian coho fishery managers to react to adverse marine survival conditions.

Résumé

Dans ce document, nous présentons un algorithme d'estimation visant à détecter rapidement des mauvaises conditions de survie en mer pour les stocks de coho des zones côtières nordiques canadiennes. Par cette méthode de modélisation, nous tentons de répartir la variation hebdomadaire des recaptures de cohos marqués (au moyen de micromarques codées) dans les pêches frontalières aux lignes traînantes en composantes qui dépendent respectivement du nombre total de saumoneaux marqués, de l'effort de pêche et des taux de survie en mer. Nous tenons compte de l'incertitude des prévisions du taux de survie en mer par un cadre décisionnel analytique bayesien qui considère le risque de surpêche. Nous nous sommes servis de données simulées pour vérifier les méthodes statistiques ainsi que l'exactitude et l'erreur systématique des prévisions.

Les prévisions rétrospectives de survie en mer se comparent bien aux estimations de la survie réelle en mer obtenues à partir d'estimations des prises et de l'échappée faites après la saison ainsi qu'à des prévisions antérieures de la survie en mer. L'algorithme a donné des alertes exactes de mauvaises conditions de survie en mer pour toutes les années où de telles alertes étaient requises. Sur 19 cas possibles, l'analyse a donné une fausse alerte, ce qui correspond à un taux d'erreur de type I de 5 %.

La procédure de prévision de la survie en mer permet de détecter de mauvaises conditions de survie en mer jusqu'à six semaines avant l'ouverture de la pêche canadienne du saumon coho, ce qui donne aux gestionnaires de cette pêche assez de temps pour y réagir.

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Introduction

The Canadian North Coast coho fishery demonstrates most of the challenges encountered in managing todays salmon fisheries. Ocean migration patterns and variable run timings expose multiple stocks of coho to incidental and directed harvest in six fisheries (seine, gillnet, troll, marine and fresh water sport, and aboriginal) operating in the U.S.A. and Canada. Inter-annual variation in freshwater and marine survival rates also make pre-season forecasting of escapement levels difficult, even for well studied stocks.

Conservation concerns over poor recruitment during the late 1990s forced coastwide closures of Canadian commercial, and some recreational, fisheries for coho salmon until spawning escapements improved. At present, coho fishery management policies continue to be conservative because stock-specific assessment and management is impractical for coho salmon in the Southeast Alaska panhandle and northern British Columbia. Two independent agency (ADFG and FOC) reports differed in their assessments of abundance trends and underlying causes, current status, and appropriate targets for escapement and exploitation for several northern British Columbia stocks (Pacific Salmon Commission 2002). This is not surprising given that individual coho stocks are dispersed over a wide geographical range, occur in many small tributary streams, and typically comprise less than a few thousand individual spawners. Precise monitoring and assessment are nearly impossible in such situations. Furthermore, long lag times between exposure to ocean fisheries and escapement enumeration several hundred kilometers upstream precludes in-season mitigation of potentially dangerous fisheries impacts.

Target exploitation rates for mixed-stock coho fisheries have recently been established at approximately 60% with the intention of rebuilding coho stocks (Holtby and Finnegan 1997). Alaskan fisheries have historically harvested 44% (1991-2001 mean exploitation) of returning Canadian coho. Therefore, the Canadian North Coast coho fishery has set a target exploitation rate of between 10% and 15% of total returns.

An in-season measure of coho marine survival or abundance would allow managers to adjust the Canadian fishery exploitation rate in response to variation in marine survival patterns over time. In-season forecasting is the primary methodology used to achieve annual exploitation rate targets in many sockeye (*Onchorhychus nerka*; Link and Peterman 1998; Cox-Rogers 1997; Fried and Hilborn 1988; Noakes 1989), atlantic (*Salmo salar*; Claytor 1996), and pink salmon fisheries (*O. gorbuscha*; Zheng and Mathisen 1998) and has been examined for British Columbia's North Coast coho (Holtby 2000).

Holtby (2000) described the following three criteria that an in-season coho forecasting method must meet: (1) it must provide dependable detection of the situation against which it is warning. The consequences of failing to detect an extremely poor survival year are to increase the risk of possibly irreversible damage to stocks that are conservation concerns. Because coho are captured in mixed-stock fisheries, those risks are actually applied to Conservation Units as well as individual spawning populations. Consequently, this is the most important of the three criteria; (2) it must provide warning in sufficient time that mitigative actions actually reduce risk. For North Coast coho, forecast advice by the end of July or first week of August would provide sufficient warning to significantly reduce the impacts of Canadian troll fisheries, which are the major Canadian harvesters of upper Skeena coho; and (3) it must provide no, or very few, false warnings that lead to disruption of the socio-economic benefits derived from coho fisheries.

It is important that an early-warning scheme detect a sea-entry year like 1996 (return year 1997), which saw record low survival and escapement over much of northern B.C (Holtby et al. 1999). Upper Skeena coho marine survivals in 1992,1995, and 1998 were also very low and given the precarious state of upper Skeena coho returning off the 1997 brood, marine survivals of comparable levels should also be detectable by any early-warning scheme.

Marine survival of north coast coho is currently forecast pre-season using time-series and sibling analysis. Post-season estimates of marine survival and harvest rates are calculated using escapement estimates and catches in Alaskan and Canadian coho fisheries. However, neither method predicted the poor marine survival of the 1997 or 1989 return years, and as a result, stocks were overfished in those years.

In this paper, we develop and test an in-season forecasting method that attempts to provide early warning of poor marine survival rates of Canadian North Coast coho stocks. Marine survival rates for a given return year are estimated from weekly catches of coded-wire tagged coho from three indicator stocks that are captured in the Alaskan boundary troll fishery. Overall performance of the estimation scheme is assessed using both simulated and actual time-series of marine survival rates. Finally, we perform a retrospective (1990-1999 inclusive) analysis of historical catch and marine survival rates in which we compare the model-derived advice to Holtby's forecasting criteria.

Methods

Coho salmon fishery data sources

Historical coded-wire tagged (CWT) coho releases and marine survival rates for Lachmach River, Toboggan Creek, and Babine River indicator systems (Fig. 1) have been documented by Holtby (2000), Holtby and Finnegan (1997), and Holtby et al. (1999)(Table 1). Upper Skeena River coho CWT recoveries and fishery catch and effort data for the boundary area troll fisheries were provided by Alaska Department of Fish and Game (Table 2; Leon Shaul, Alaska Department of Fish and Game, Commercial Fisheries Division, Douglas, Alaska, personal communication). Marine survival rates were transformed to the logit scale for the non-linear estimation procedures described below (Fig. 2).

In-season CWT catch model

We developed a simple removal model to predict coho salmon abundance and catches for each year and week of fishing in the boundary troll area given the number of CWTs initially released, marine survival for each stock and return year, and troll fishing effort for each week and year. The predicted catch of stock j CWTs for year t and week w is (see Table 3 for notation)

$$\hat{C}_{j,t,w} = N_{j,t,w}(1 - e^{-q_{j,w}E_{t,w}}) \qquad (1)$$

where the predicted number of CWT coho available to the fishery during week w is

$$N_{j,t,w} = s_{j,t}R_{j,t} - \sum_{i=1}^{w-1} \hat{C}_{j,t,i} \qquad (2)$$

Posterior distribution for marine survival rates

We assumed that the weekly CWT catches follow a Poisson distribution which has the following log-likelihood function (ignoring additive constants that depend only on the data)

$$\ln L = \sum_{j=1}^{J} \sum_{i=1}^{t} \sum_{k=1}^{w} \hat{C}_{j,i,k} \ln C_{j,i,k} - \hat{C}_{j,i,k} \tag{3}$$

In the sections below, we refer to the above likelihood component (3) of the overall posterior distribution as L.

Multivariate normal prior distribution

Inter-annual variation of logit transformed marine survival rates for the three stocks in our analysis are highly correlated (Fig. 3). We expected that accounting for such a high degree of covariation among stocks would improve in-season forecasts because low survival experienced by one stock should imply low survival for most other stocks as well. For example, if low observed CWT recoveries for two stocks indicated low marine survival in a given year, then high CWT recoveries for another stock should be discounted as possibly arising from random errors in catch rates rather than particularly high marine survival. We accounted for correlated marine survival by incorporating a multivariate normal prior distribution on logit-transformed survival rate deviations from their stock-specific means. The multivariate log-prior is of the form

$$\ln MVN(\mathbf{s}^{*}_{t,w}) = \sum_{i=1}^{i=t} \mathbf{s}_{i,w} \Sigma^{-1} \mathbf{s}_{i,w} \tag{4}$$

where Σ^{-1} is the known covariance matrix inverse of logit-transformed marine survival rate deviations for the three stocks and $\mathbf{s}^*_{i,w}$ is the vector of logit-survival rate deviation estimates for year i and week w. Note that the likelihood (3) and multivariate prior (4) components are both written in retrospective form; that is, estimation of marine survival for year t given the catch data up to week w only takes into account the data prior to that year and week.

Assuming a uniform $U(-\infty, +\infty)$ prior distribution for the matrix of log-catchability parameters $\mathbf{Q}_{t,w}$, the log-posterior distribution for the marine survival and catchability parameters in year t is

$$\ln LMVN\left(\mathbf{s}^*{}_{t,w}, \mathbf{Q}_{t,w} | \mathbf{C}_{t,w}, \Sigma\right) \propto \ln L + \ln MVN\left(\mathbf{s}^*{}_{t,w}\right) \tag{5}$$

where the subscripts indicate that the posterior distribution is evaluated using only the data up to the current year and week. In the sections below, we refer to the multivariate log-posterior as LMVN, indicating that it is composed of a Poisson likelihood (L) and multivariate normal prior (MVN).

Independent normal prior distributions

An alternative formulation to the log-posterior (5) is to assume that annual marine survival rates are independent (i.e., all among stock covariance terms set to zero in Σ). For this case, the log-prior takes the form

$$\ln N(\mathbf{s}^*_{t,w}) = \sum_{j=1}^{J} \sum_{i=1}^{i=t} \frac{s^2_{i,j,w}}{2\Sigma_{jj}}. \tag{6}$$

Combining the likelihood and normal prior give the the following log-posterior distribution for independent marine survival rates

$$\ln LN\left(\mathbf{s}^{*}{}_{t,w}, \mathbf{Q}_{t,w} | \mathbf{C}_{t,w}, \Sigma\right) \propto \ln L + \ln N\left(\mathbf{s}^{*}{}_{t,w}\right). \tag{7}$$

We refer to this log-posterior distribution as LN, indicating that it is composed of the Poisson likelihood (L) and an indpendent normal prior (N) on the annual survival rates.

Simulation tests of model performance

We tested overall performance of the marine survival estimation scheme by generating 100 simulated datasets of marine survival and CWT catch data for the three stocks. Actual CWT releases (Table 1) and boundary troll weekly fishing effort (Table 2) were used to generate expected CWT returns using (2) and (1) with catchabilities set equal to the stock specific estimates from initial runs of the full model on actual data. Random variation in marine survival rates was generated using three types of multivariate normal distribution in which among stock correlations were set equal to $0.2, 0.5$, and 0.8. The last case ($\rho = 0.8$) is representative of the actual covariation among the three coho stocks. Multivariate normal distributions were generated by first specifying a correlation matrix $\mathbf{R}$ and a diagonal matrix $\mathbf{A}$ in which the diagonal elements are equal to the stock-specific standard deviations of marine survival. From these two matrices, we computed the resulting covariance matrix $\mathbf{S}$ as

$$\mathbf{S} = \mathbf{ARA} \tag{8}$$

Multiplying the choleski decomposition of $\mathbf{S}$ times a vector of standard independent normal random draws provides a correlated vector of simulated logit-survival rates for a given year. The resulting realized matrix of logit-survival rates for each simulation was then passed to the estimation scheme to construct the observed covariance matrix Σ (i.e., our simulated estimation scheme knew only the covariance matrix of logit-marine survival rates).

We simulated the catch process by drawing random CWT catches from Poisson distributions with expected values equal to those specified by the catch equation (1).

Simulated marine survival rate time-series were then estimated for each dataset using each of the objective functions (L, LN, and LMVN) and a known Σ as described above. We examined the degree of precision and bias in the estimates arising from each objective function by fitting generalized linear models to the estimated versus true marine survival rates. Linear models were constructed on the logit-survival scale so that that normally distributed errors could be assumed.

Generating the full posterior distributions from actual data

After choosing the appropriate objective function for analysis of actual marine survival rates, we performed a full Bayesian retrospective analysis of historical CWT catch data. Posterior distributions for all parameters were generated using a two-step procedure in which a Quasi-Newton routine (Otter Research Ltd. 2000) first minimized the (negative) log-posterior in equation (5) and estimated the approximate variance-covariance matrix for the catchability and logit-survival parameters. Then we initiated four Markov Chain Monte Carlo (MCMC) sequences in which the starting parameter values for each sequence were 2.0, 1.0, -1.0, and -2.0 standard deviation units from the modal value for each parameter. Convergence of the MCMC sequences to their target posterior distributions was assessed using the potential scale reduction method described in Gelman et al. (1995). The scale reduction technique performs an analysis of variance for cluster sampling in which the variance among MCMC sequences is compared to the variance within sequences. A statistic $\Re_n$ is computed that represents the potential reduction in scale of the current posterior distribution that would occur if the sample size n (i.e., number of MCMC samples) were increased to infinity. Theoretically, $\Re$ should decrease to 1 in the limit $n \longrightarrow \infty$. However, for most practical situations a value of $\Re \leq 1.2$ is generally considered an acceptable indication of convergence (Gelman et al. 1995). For convergence testing, we ran $2,000,000$ MCMC iterations and sampled every 100th value for a total of $20,000$ posterior sample points.

Upon convergence of MCMC sequences for all parameters, we discarded posterior samples prior to convergence and considered the remaining sample points as representative of the posterior distributions. Posterior samples of log-catchability and logit-survival parameters were then back-transformed to their natural scales $(0,\infty)$ and (0,1), respectively.

Posteriors were summarized into histogram form from which the probabilities for marine survival rates were computed for each week and year (but only dependent upon data prior to and including that week and year). We then computed the cumulative probability that marine survival for each stock was less than a critical value $S_{crit,j}$ as defined below.

Retrospective decision analysis

For each week during the preseason, the above procedure generated the probability $p_{j,t,w}$ that marine survival for the current year is less than or equal to the critical value required to open the Canadian fishery. The probability that marine survival is greater than the critical value is just $1 - p_{j,t,w}$. For our analysis, we used critical survival rates $S_{crit,j}$ equal to 50% of the mean 1988 to 1999 survival rates for each stock. These values correspond to the extremely poor marine survival rates that occurred in 1989, 1997, and 1998, and are equivalent to those defined by Holtby (2000). The specific values used for Toboggan Creek, Lachmach River, and Babine River coho are 0.020, 0.025, and 0.120, respectively.

Given a set of CWT catch data, there are two possible errors that could arise from a decision to open or close the Canadian coho fishery based on the above analysis: (1) a Type I error, which involves concluding (incorrectly) that marine survival is less than the critical value when in fact it is actually greater, and (2) a Type II error, which involves concluding that marine survival is not less than S_{crit} when in fact it actually is. A Type II error in the coho situation leads to immediate overfishing, loss of long-term harvest value, and failure of conservation-based management. In contrast, a Type I error, while sacrificing short-term harvest, may actually lead to higher long-term harvests if the consequent increase in escapement leads to higher returns and catch in the future. In the context of decision making, it is usually prudent to explicitly recognize these costs or losses associated with committing various types of errors. For example, a fisheries manager attempting to meet both harvest and conservation objectives might treat overfishing risks (i.e., Type II errors) more seriously than the risk of short-term losses in catch (i.e., Type I errors) because overfishing typically has more serious long-term biological, and likely sociological, consequences. Characterizing the implied (or realized) losses that managers expect from different errors can be achieved by a simple decision matrix **D** (Table 4) in which relative costs are assigned to the alternative types of errors. We assigned a relative cost of 2 for overfishing (Type II) errors in our analysis and Type I errors were assigned a cost of 1, which reflects a lower, but still substantial, cost of error.

Our retrospective decision analysis involved generating model estimates and management advice for year t and week w using only the data for years $1, \ldots, t-1$ (data for all weeks was used prior to t) and weeks $1, \ldots, w$ in year t. For each year and week we first generated posterior distributions for all model parameters from which we computed probabilities for the alternative possibilities (i.e., states of nature) that true marine survival is either less than $S_{crit,j}$ ($p_{j,t,w}$) or greater than or equal to $S_{crit,j}$ ($1 - p_{j,t,w}$). We then assigned these probabilities to the two elements of a vector $\mathbf{P}_{j,t,w}$. The vector of expected costs associated with making a management decision to open the Canadian fishery or not was then computed as $\mathbf{U}_{j,t,w} = \mathbf{D}\mathbf{P}_{j,t,w}$. The optimal decision that a rational manager would make based on the data for stock j in year t and week w is the one corresponding to the smallest element of $\mathbf{U}_{j,t,w}$. We show an example of this calculation in the retrospective analysis results section below. A schematic diagram showing the flow of the in-season estimation algorithm is shown in Figure 4.

Results

Simulation testing of estimation methods

Simulated estimates of marine survival rates were extremely biased when the objective function included only the Poisson likelihood (Fig. 5; $\rho = 0.8$). For this case, most of the variation in CWT catches was assigned to marine survival rates, which tended to be rather strongly overestimated. Including the multivariate normal prior improved estimation precision and bias considerably over the Poisson likelihood alone. The LMVN posterior function showed the lowest overall bias, which is indicated by an average slope between true and estimated logit-survival rates of approximately 0.96 (Table 5) (Fig. 6; $\rho = 0.8$). LMVN bias tended to increase (greater under-estimation) as the simulated correlation among stocks increased from 0.2 to 0.8. The independent normal prior and Poisson likelihood (LN objective function) generated a small average underestimation bias of approximately 0.92 (Fig. 7; $\rho = 0.8$). The LN posterior function bias was unaffected by the actual degree of correlation among survival rates of the different stocks, whereas estimation performance for the LMVN case degraded as the degree of correlation among stocks increased (Table 5). More importantly however, the LN objective function resulted in the lowest AIC values for all among-stock correlations examined (Table 5). Lower AIC values reflect lower differences among stock in estimation performance. For example, as the among-stock correlation increased from 0.2 to 0.8, the differences in bias among stocks actually increased for the LMVN posterior, whereas these differences were always small for the LN posterior. Given the better overall performance and the fact that biases were similar for both posteriors when correlations were high (as is true in the actual coho data), we used the independent normal prior assumption (LN objective function) for further analyses.

Catchability and marine survival estimates

Residual functions show that the estimation procedure performs reasonably well in predicting weekly catches, especially for low abundance years when reliable forecasts are needed. This is evident in an aggregated plot (i.e., all stocks, weeks, and years combined) of residuals against predicted values (8), which shows that absolute errors are generally proportional to predicted CWT catches. Although this would typically indicate that a log-normal likelihood function be used, frequent occurrences of zero catches would complicate the use of such a function. In general, it appears that the Poisson likelihood combined with an independent prior distribution provided reasonable precision at low coho abundance. Prediction errors at higher abundance are not a concern at this point because our purpose is to identify low abundance/survival years only.

Weekly stock-specific catchability

Catchability parameters for all three stocks showed a similar pattern of increasing catchability during the early weeks of the boundary troll fishery followed by decreases in later weeks (Fig. 9). This pattern likely reflects availability of coho as they migrate through the boundary troll fishing area enroute to the Skeena River. Catchability for Babine coho showed the least variation among weeks and was on average approximately twice as high as those of Toboggan and Lachmach stocks (Fig. 9; right-hand axes). Coefficients of variation for catchability estimates derived from the approximate variance-covariance matrix ranged from 20% to 50% with Babine being highest and Lachmach the lowest.

Marine survival rates

Marine survival rate estimates derived from the CWT catch and survival model corresponded reasonably well to the observed marine survival rates for all stocks (Fig. 10). The most noteworthy concern with our marine survival rate estimates is an apparent shift from negative to positive residual errors between estimated and actual marine survival rates for the Lachmach stock (Fig. 11). The shift and subsequent run of four positive residuals beginning in 1996 suggests that either mean fishery catchability changed rather abruptly after 1995, or that changes in escapement or catch enumeration methods occurred after 1995. Neither of the other two stocks show evidence of a major change in fishery catchability during the same period. Therefore, we concluded that the actual marine survival rate data for Lachmach coho contain systematic measurement errors. Such errors are consistent with a change in smolt capture methods from trapping fences, which are generally not size-selective, to minnow traps, which tend to be selective toward smaller smolts (B. Holtby, Fisheries and Oceans Canada, Pacific Biological Stations, personal communication). Thus, the residual pattern estimated by the model probably reflects a size-dependent survival effect.

Retrospective Bayesian decision analyses

We performed the MCMC convergence test for several stock/year/week combinations and the results were generally similar among trials. Results for the first week of boundary troll fishing in 1993 (i.e., $t = 6$ and $w = 1$ in Equation (5) for year 6) are indicative of overall convergence behaviour. For this case, the MCMC algorithm converged on the posterior distributions for most catchability and survival rate parameters within approximately 2000 samples (i.e., 200,000 iterations) (Fig. 12). The only exception was Babine catchability, which required approximately 4000 samples before convergence was achieved (Fig. 12e). Longer convergence time was mainly the result of higher uncertainty associated with Babine catchability parameters relative to the other stocks (Fig. 9c).

In-season forecasts of marine survival (posterior means) generally stabilized by the third week of boundary troll fishing. Although estimates during the first week were the most variable, in most cases, estimates monotonically approached the post-season estimates as the fishing season progressed (Figs. 13, 14, and 15). In-season estimates were also within approximately 20% of the actual marine survival rates in many cases. Babine survival rates in 1994 and 1996 were both rather highly underestimated; however, as we show below, neither forecast resulted in an erroneous marine survival warning.

Cumulative probability plots show the dynamics of weekly uncertainty about marine survival rates for all stocks and years (Figs. 16, 17, and 18). The steepness of the cumulative probability curves is proportional to the level of certainty about marine survival rate estimates from the assessment model. In years for which an early warning is required (i.e., plots with double asterisks), the estimation scheme shows a strong degree of certainty that marine survival rates were indeed low. In general, estimates during early weeks reflected a greater degree of uncertainty than those in later weeks and only rarely did the uncertainty increase as the fishing season progressed (e.g., Fig. 16; 1992).

The full Bayesian decision analysis detected all seven stock/year combinations for which marine survival rates were less than the critical survival values. Six out of the seven correct warnings were clearly obvious based on the first week of troll fishing (Fig. 19 and 21). In the exceptional year, it was relatively clear that the cost functions were conflicting by the second week, which would warrant a precautionary approach. Such conflicting cost functions, where neither dominates the other, resulted from a combination of moderate uncertainty, marine survival rate estimates that were near the critical survival region, and the costs we associated with alternative types of errors. Babine survival estimates for 1996 are indicative of how conflicting cost functions arise. From the cumulative probability distribution (Fig. 18; 1996), there was an approximate 30% chance that survival was less than 0.0125 and a 70% chance that marine survival was greater. Therefore, the cost of concluding that marine survival was less than or equal to the critical survival rate is $(0)(0.3)+(1)(0.7) = 0.7$, whereas the opposite conclusion is $(2)(0.3)+(0)(0.7) = 0.6$ (these values represent the elements of the cost matrix $\mathbf{U}_{j,t,w}$). Being nearly equivalent, these apparent costs indicate that the data do not clearly support one or the other conclusion.

The Bayesian analysis provided only one false warning, which in fact was a relatively strong one for Toboggan Creek in 1993 (Fig. 19). Interestingly, a warning was also provided for Babine in the same year; however, we do not have actual marine survival estimates for Babine in that year to determine whether this was a valid response.

Discussion

In this paper, we developed an estimation algorithm that is intended to provide early warnings of poor marine survival conditions for Canadian North Coast coho stocks. The modelling approach attempts to partition the variation in observed CWT coho catches in boundary troll fisheries into components that depend upon total CWT coho smolts released, troll fishing effort, and marine survival rates. The approach compared favorably with actual marine survival estimates obtained from post-season catch and escapement estimates and with previous assessments that attempted to forecast marine survival (Holtby

2000). In particular, the algorithm provides reasonably accurate warnings of poor marine survival conditions that allow sufficient time for Canadian coho fishery managers to react.

The early warning scheme developed in this paper appears to meet all three Holtby (2000) forecasting criteria. (1) *Dependable detection* - the algorithm successfully detected all critical survival years for all stocks using only the data prior to that year. The retrospective approach only provided the estimation algorithm with the types of information we would normally have available for forecasting, which, for early years, means that the algorithm operated efficiently on a limited amount of data. (2) *Provide sufficient reaction time* - six out of the seven correct warnings were clearly obvious after only one week of troll fishing. Such a lead time (six weeks) would allow managers to assess Canadian coho fishery options. In the exceptional year it was relatively clear that a precautionary approach was warranted because the cost functions were conflicting by the second week, or five weeks prior to the Canadian fishery. (3) *Provide very few or no false warnings* - the forecasting procedure provided only one false warning (Toboggan Creek, 1993). One false warning from 19 possible cases (those for which actual $s_{j,t} > S_{crit,j}$) corresponds to an approximate 5% Type I error rate, which is a widely accepted standard in scientific assessment and experimentation. This is encouraging given that we have also controlled the more important Type II error rate in this assessment.

Although we expected that accounting for correlation among stocks in marine survival would improve in-season forecasts, our simulation results showed that independent priors on marine survival rates performed as well as including among-stock correlation information. In general, the multi-variate normal prior showed lower average bias, however this resulted from averaging rather substantial positive and negative estimation biases among stocks. This was somewhat surprising given the fact that the simulated survival data were actually generated from a multivariate normal distribution for which the LMVN posterior function had a very good estimate. Using the multivariate prior would have probably lead to a higher Type I error rate for some stocks, especially in those cases where marine survival rates were low but not critical.

Despite the encouraging performance at this point, our forecasting procedure could probably be improved. In its present form, the estimation scheme takes no account of specific marine survival rates that actually occurred in years prior to the forecasting year; in other words, the model only accounts for past CWT catches, and only the covariance matrix of historical survival is assumed known. This approach ignores a significant amount of available information. We believe the model could be improved by using actual marine survival rate estimates obtained post-season to update catchability parameters via a Kalman filter. Such an updating procedure would allow the estimation scheme to track catchability trends. Although no strong catchability trends existed for the stocks in our analysis, it is not unlikely that fishing power will change in the future as target species change (e.g., from coho to chinook). Attempting to track catchability would also be wise if catchability varies with coho abundance (i.e., is density-dependent) (Martell and Walters 2002).

Another obvious way to improve this analysis is to include more test fisheries. We only used the Alaskan boundary troll fishery, however several other test fisheries are available. The framework we developed would easily accommodate existing gillnet test fisheries as well. Combining all information sources in one analysis is relatively straightforward within the our approach, and would be preferred over choosing one among several possible test fishing indices.

Although we did not show exploitation rate estimates, these are provided by our analysis. Therefore, in addition to providing estimates of marine survival rates, the analysis could be used to forecast ultimate exploitation rates in Alaskan fisheries up to six weeks in advance of the Canadian fishery. In years of low (though not critically low) abundance, forecasts of Alaskan fishery exploitation rates would allow in-season adjustments to Canadian quotas to protect against overfishing stocks such as Babine coho, which tend to be heavily exploited in Alaskan fisheries (i.e., high mean catchability).

Implications for indicator stock monitoring

A primary objective of North Coast coho management is to protect the current level of coho stock diversity (Fisheries and Oceans Canada 2000). Reliable indicator stock monitoring programs are a tactical means of achieving such an objective. A systematic search for informative indicator stocks should attempt to find those stocks that provide several key bits of information. First, indicator stocks should provide information about long-term production effects of fishing, which implies that indicator stocks should represent the range coho productivity. While certainly not a new observation, it is important that the indicator program provide advice for all stocks, including the weaker ones. Second, indicator stocks must provide adequate tactical information about within-year run timing. Stocks with high catchability in test fisheries provide the most reliable forecasts of marine survival and exploitation rates. Low catchability typically causes greater uncertainty for in-season forecasting using any method. Finally, stocks should represent the range of average marine survival and inter-annual variation. Our simulation tests showed that prior information about marine survival rate variation greatly improves forecasting performance. Because we don't expect LMVN type models to improve forecasting, we only need estimates of marine survival rate variances for each stock. A first step toward identifying new indicator stocks could be estimation of population distributions of survival rate variances using Bayesian meta analysis methods. Such an information package for North Coast coho could provide a reasonable basis for setting weekly harvest rates in Canadian coho fisheries that would be consistent with conservation and overall harvest objectives.

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Table 1: North coast coded-wire tagged (CWT) coho releases $R_{j,t}$, boundary troll CWT catches $C_{j,t,.}$(”.” indicates the sum of catches over all weeks), and marine survival rates $s_{j,t}$.

	Toboggan			Lachmach			Babine		
Year	$R_{1,t}$	$C_{1,t,.}$	$s_{1,t}$	$R_{2,t}$	$C_{2,t,.}$	$s_{2,t}$	$R_{3,t}$	$C_{3,t,.}$	$s_{3,t}$
1988	31749	14	0.021	1169	1	0.030	31019	46	NA
1989	30354	135	0.027	9481	85	0.042	29004	332	NA
1990	31300	180	0.041	17210	415	0.132	31139	221	NA
1991	30954	421	0.060	24408	571	0.124	30362	269	NA
1992	31290	127	0.017	13186	243	0.094	31497	115	NA
1993	60542	155	0.029	19921	206	0.066	30979	163	NA
1994	32600	344	0.060	14055	484	0.188	30753	240	0.040
1995	33533	65	0.018	6276	76	.086	32934	133	0.010
1996	33609	237	0.025	3629	101	.104	29255	191	0.031
1997	32368	30	0.005	5234	73	0.043	29694	26	0.006
1998	33255	56	0.018	7645	148	0.095	59891	120	0.007
1999	33935	413	0.104	11722	346	0.125	59965	767	0.051

Table 2: Total troll fishing effort in the Alaskan boundary troll fishery. Effort units are thousands of power-troll equivalent boat days.

	Week					
Year	1	2	3	4	5	6
1988	1.51	6.59	5.95	3.32	1.59	1.45
1989	5.55	6.39	4.47	6.38	6.55	5.49
1990	4.70	4.82	5.93	4.34	5.34	4.81
1991	3.87	4.71	3.53	3.95	3.61	3.64
1992	2.66	1.07	3.40	4.38	3.86	4.49
1993	1.10	3.69	3.21	4.51	4.19	5.02
1994	0.57	4.22	3.67	4.01	5.08	5.29
1995	3.37	3.02	2.67	2.95	3.94	4.58
1996	2.68	3.12	2.57	3.13	3.51	3.29
1997	2.73	2.45	2.25	3.21	3.19	2.24
1998	1.88	3.05	2.41	2.97	2.79	2.80
1999	1.45	2.32	2.49	2.65	2.62	3.18

Table 3: Notation used for modelling and analysis of coho salmon coded-wire tag catches and marine survival.

Indices	Description
t	index for year. $t = 1, 2, ...T$
j	index for stock. $j = 1, 2, ..J$
w	index for week. $w = 1, 2, ...W$
Data	
$R_{j,t}$	number of coded-wire tagged coho released for return year t
$C_{j,t,w}$	observed catch for stock j, in year t, and week w
$E_{t,w}$	observed troll fishing effort in year t for week w
Estimated Parameters	
$s^*_{j,t}$	logit transform of marine survival for stock j in year t
$q^*_{j,w}$	logarithm of troll fishery catchability for stock j during week w (assumed constant across years)
Derived Parameters	
$s_{j,t}$	marine survival for stock j in year t
$q_{j,w}$	troll fishery catchability for stock j during week w
Predicted States	
$N_{j,t,w}$	predicted number of coded-wire tagged coho present for stock j in year t and week w
$\hat{C}_{j,t,w}$	predicted catch for stock j, in year t, and week w

Table 4: A management cost function for all possible states of nature (columns) and conclusions (rows) drawn from the data. The upper left entry (0) under "State of Nature" indicates that if the true marine survival rate is less than or equal to $S_{crit,j}$ and a conclusion $s_{j,t} \leq S_{crit,j}$ is made, no error is committed and the cost equals zero. However, if true marine survival is less than or equal to $S_{crit,j}$ and a conclusion $s_{j,t} > S_{crit,j}$ is made (lower left), then a Type II error is committed and a cost of two is assigned. The upper right entry (1) represents the case in which true marine survival is greater than $S_{crit,j}$, but a Type I error is committed by concluding that $s_{j,t} \leq S_{crit}$. The final entry in the lower right (0) represents the cost of a correct decision that $s_{j,t} > S_{crit,j}$.

	State of Nature	
Conclusion	$s_{j,t} \leq S_{crit,j}$	$s_{j,t} > S_{crit,j}$
$s_{j,t} \leq S_{crit,j}$	0	1
$s_{j,t} > S_{crit,j}$	2	0

Table 5: Simulation test results comparing survival rate estimates to true values generated from alternative multivariate normal distributions. Objective functions are likelihood only (L), likelihood with independent normal priors (LN), and likelihood with multivariate normal prior (LMVN). For each set of simulations correlation coefficients (ρ) for generating true survival rates were all set equal to the values indicated. Slopes relating estimated to true survival rates were estimated on the logit scale. The lowest Akaike Information Criterion values (AIC) indicate the best fitting models.

Objective function	ρ	Slope	AIC
L	0.2	1.60	13772
LN	0.2	0.92	-2404
LMVN	0.2	0.97	-1816
L	0.5	1.60	13689
LN	0.5	0.92	-2652
LMVN	0.5	0.95	-1747
L	0.8	1.63	13674
LN	0.8	0.93	-2952
LMVN	0.8	0.94	-1640

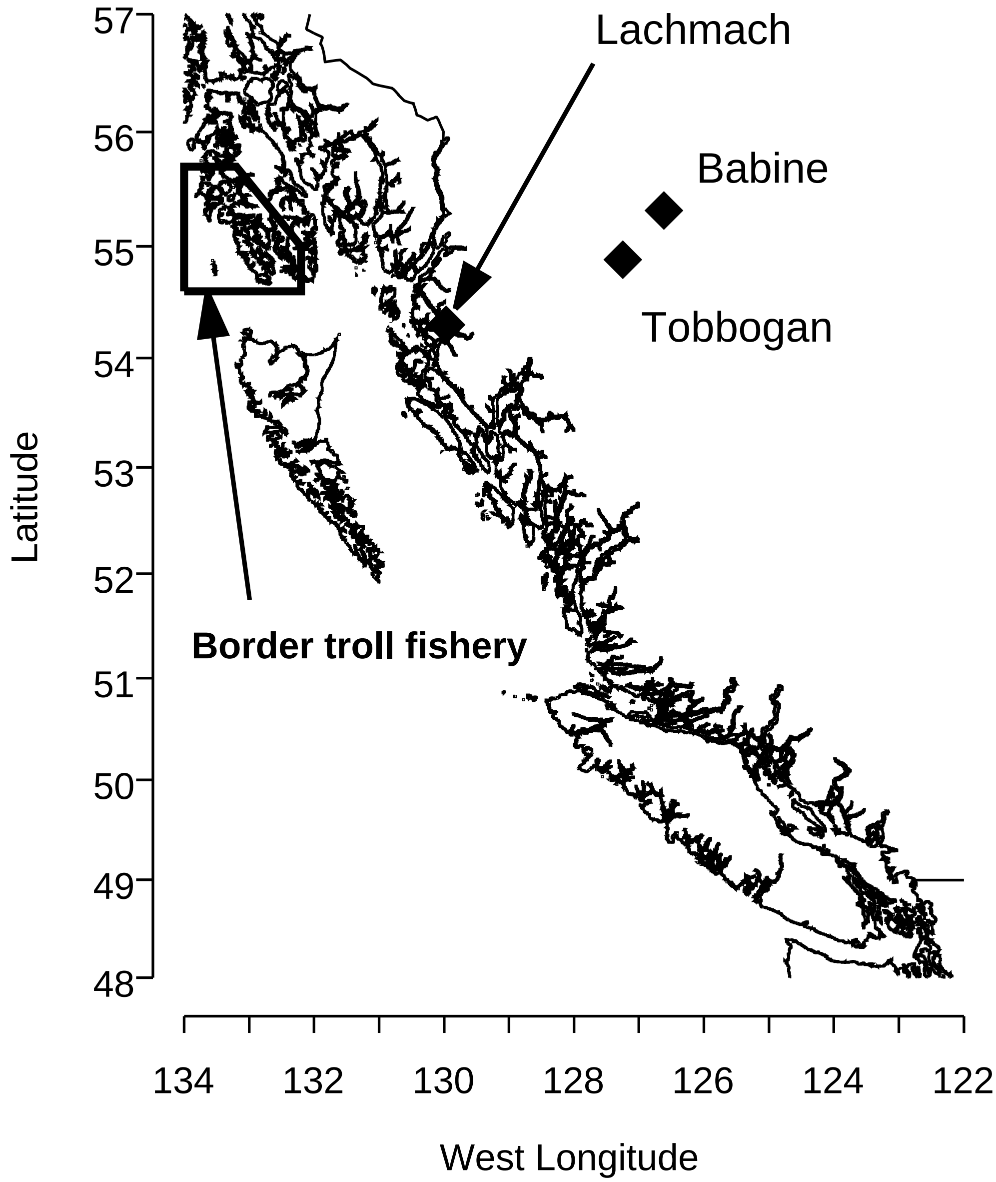


Figure 1: North coast of British Columbia and southeast Alaska

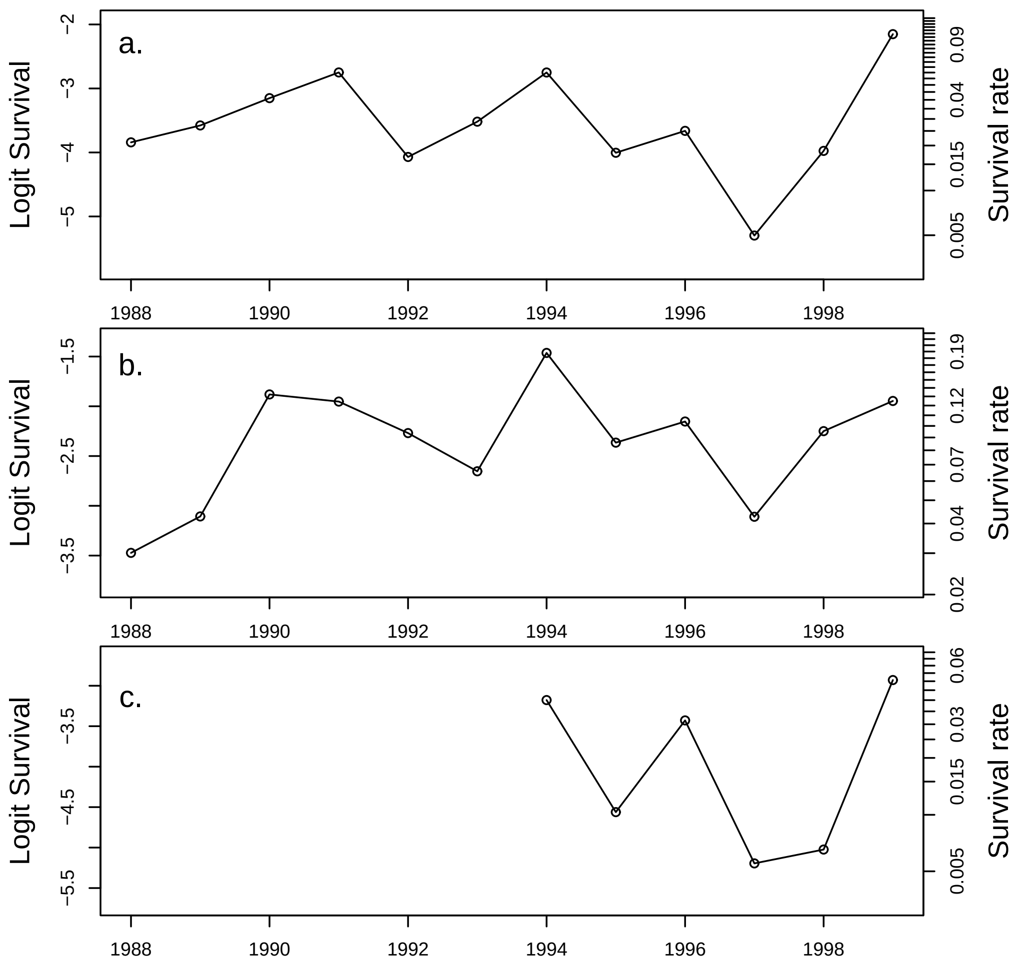


Figure 2: Logit-transformed marine survival rate estimates for (a) Toboggan Creek, (b) Lachmach River, and (c) Babine River coho (1988-1999). Marine survival rate values on the natural [0,1] scale are shown on right.

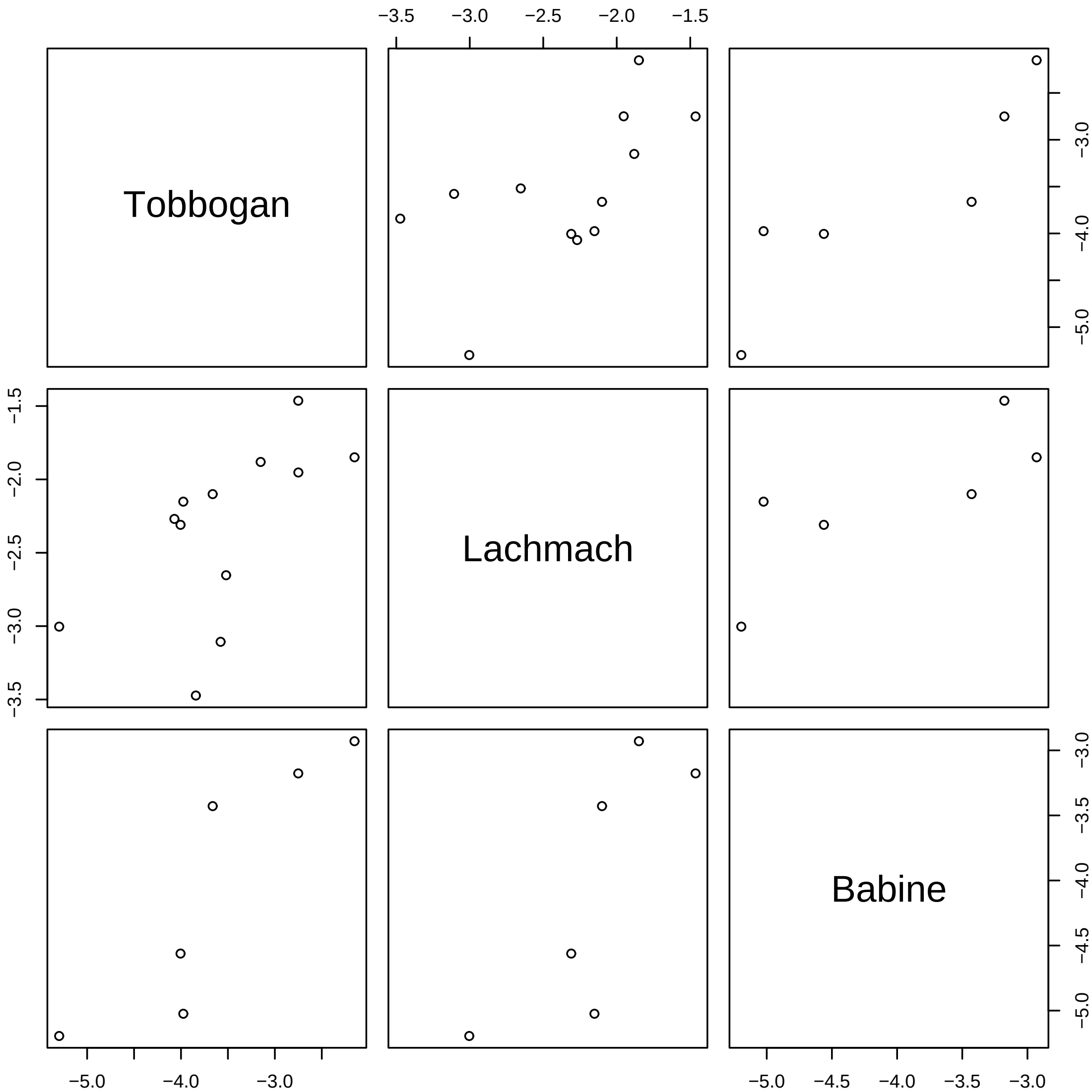
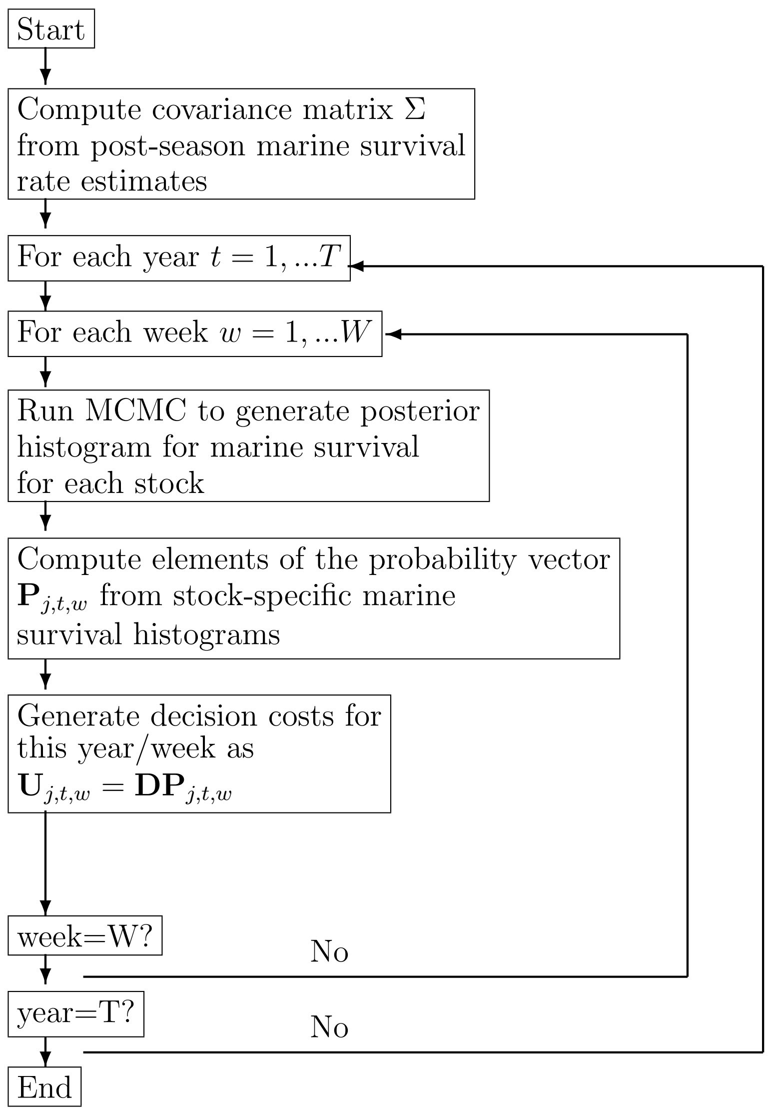


Figure 3: Correlation plot matrix of logit-transformed survival rates for Toboggan, Lachmach, and Babine coho. Correlation coefficients are $r = 0.61$ (Toboggan-Lachmach), $r = 0.89$ (Toboggan-Babine) and $r = 0.79$ (Lachmach-Babine)

Figure 4: Schematic diagram of the in-season marine survival estimation algorithm.



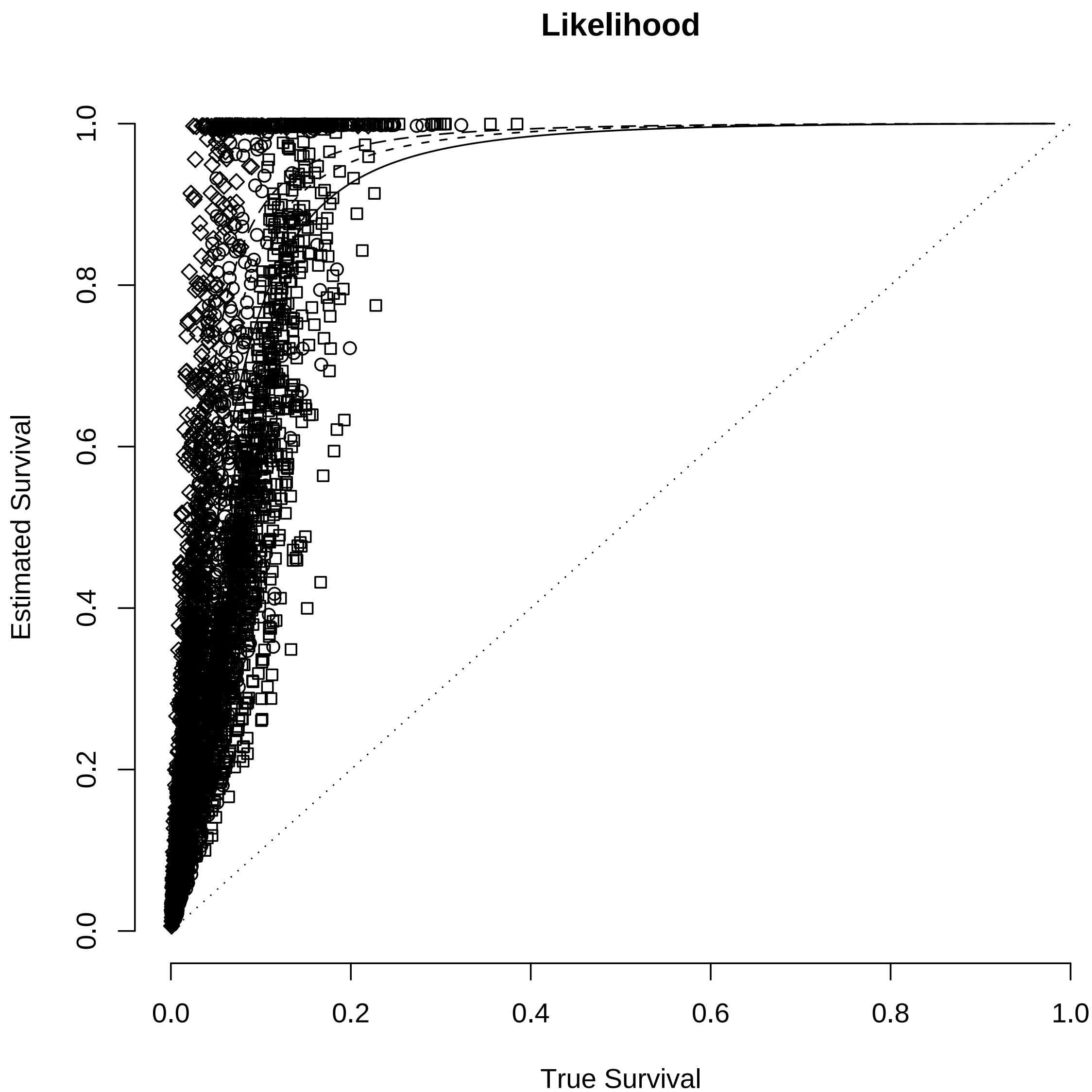


Figure 5: Simulated performance of marine survival estimation scheme for an objective function incorporating the Poisson likelihood only. The observed covariance matrix was used to generate annual marine survival rate deviations. Fitted lines are back-transformed generalized linear model fits to the Estimated versus True logit-survival rates for Toboggan (circles; solid line), Lachmach (squares; dashed line) and Babine (triangles; long dashed line). The degree of departure away from the diagonal line indicates the degree of bias in estimates.

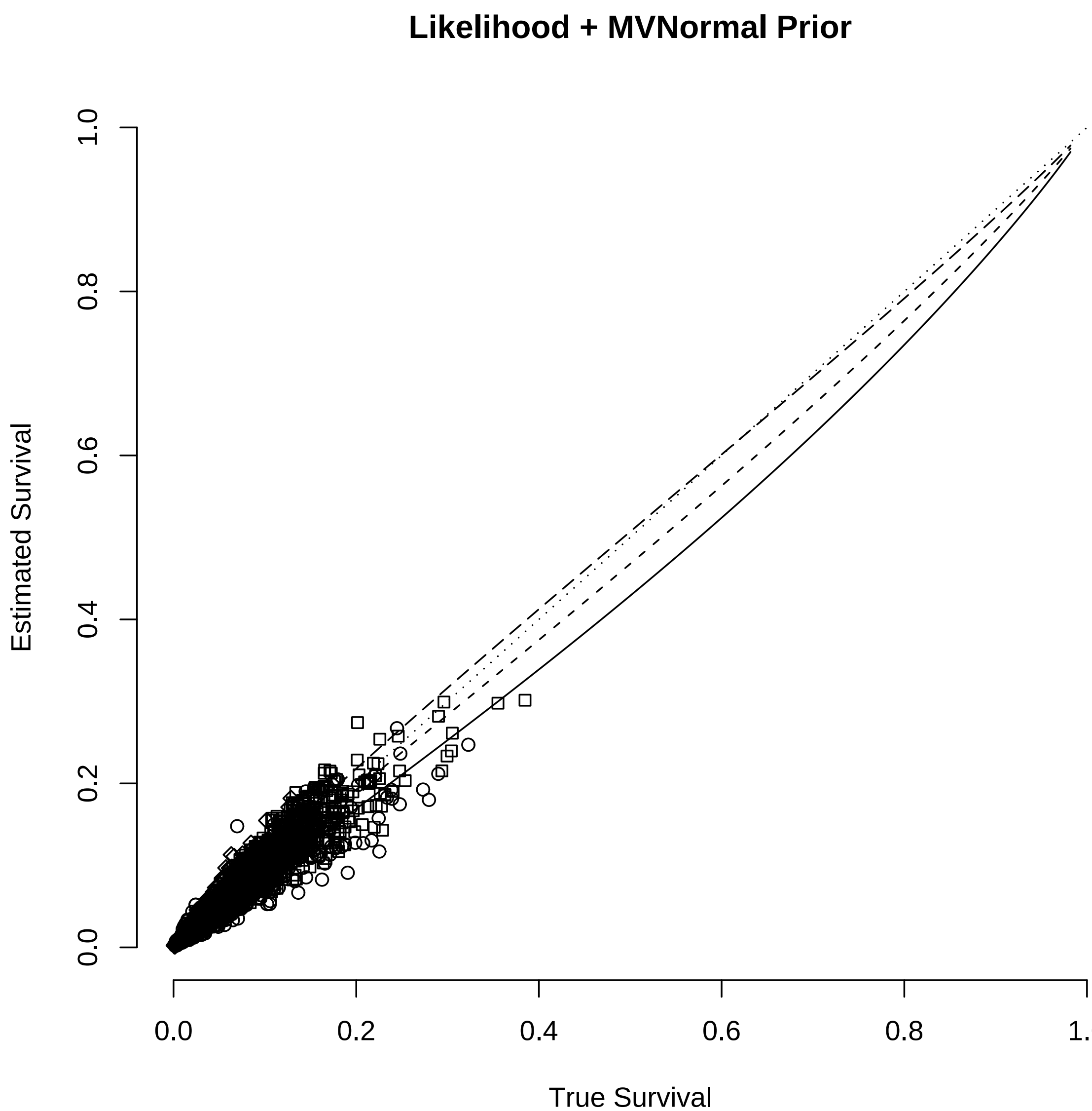


Figure 6: Simulated performance of marine survival estimation scheme for an objective function incorporating the Poisson likelihood and multi-variate normal prior. The observed covariance matrix was used to generate annual marine survival rate deviations. Fitted lines are back-transformed generalized linear model fits to the Estimated versus True logit-survival rates for Toboggan (circles; solid line), Lachmach (squares; dashed line) and Babine (triangles; long dashed line). The degree of departure away from the diagonal line indicates the degree of bias in estimates.

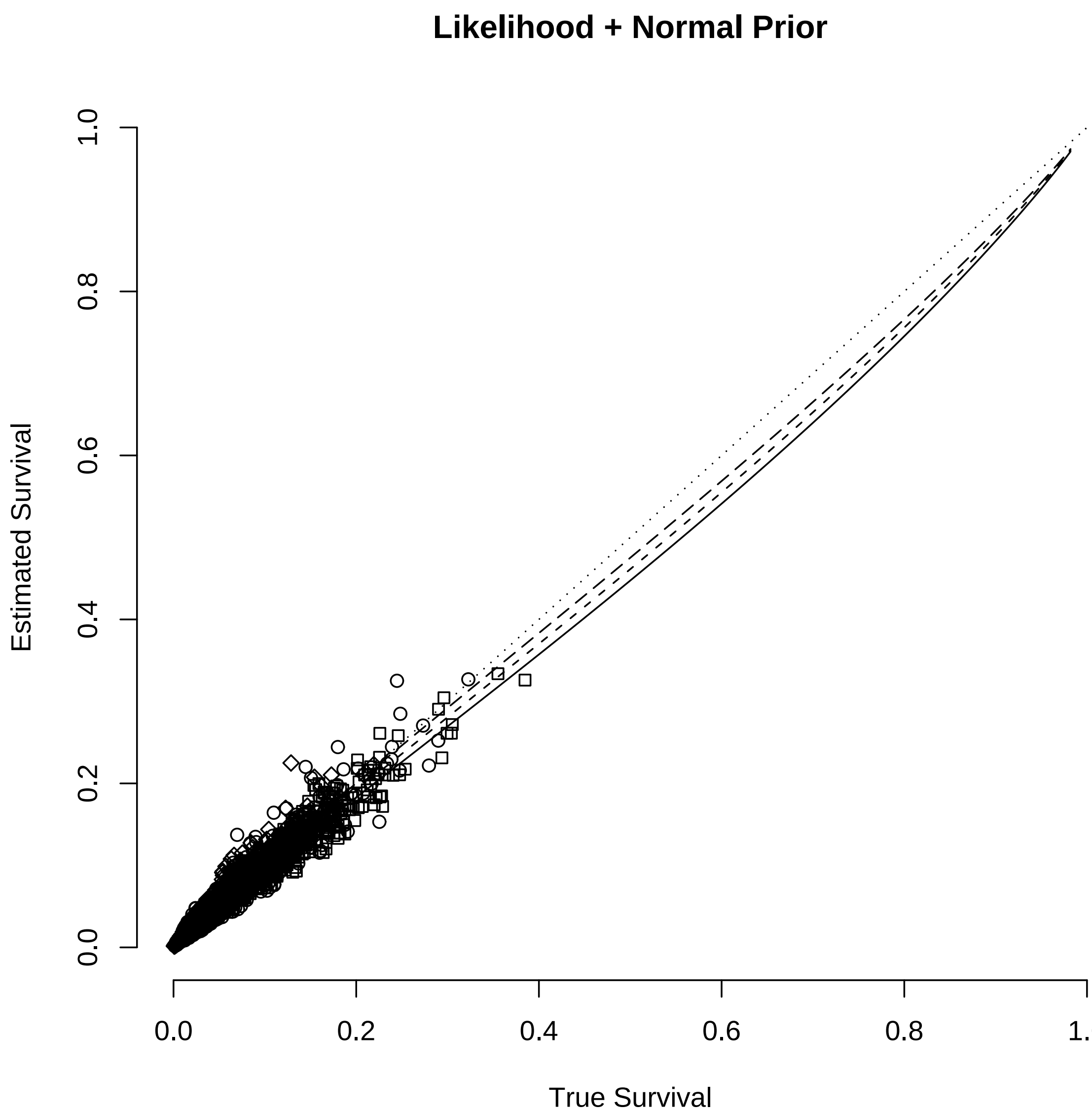


Figure 7: Simulated performance of marine survival estimation scheme for an objective function incorporating the Poisson likelihood and independent normal priors. The observed covariance matrix was used to generate annual marine survival rate deviations. Fitted lines are back-transformed generalized linear model fits to the Estimated versus True logit-survival rates for Toboggan (circles; solid line), Lachmach (squares; dashed line) and Babine (triangles; long dashed line). The degree of departure away from the diagonal line indicates the degree of bias in estimates.

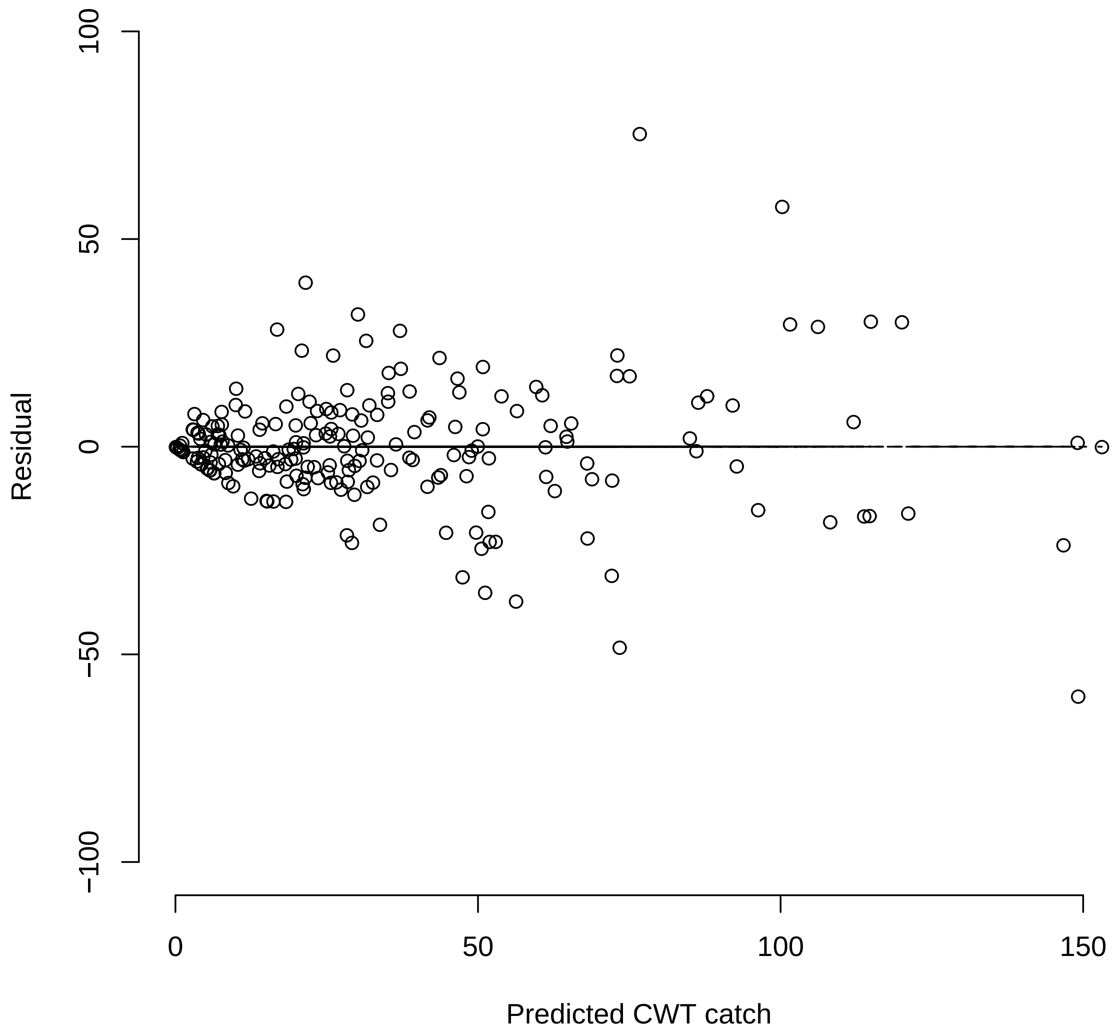


Figure 8: Aggregated residual deviations between predicted and observed CWT catches

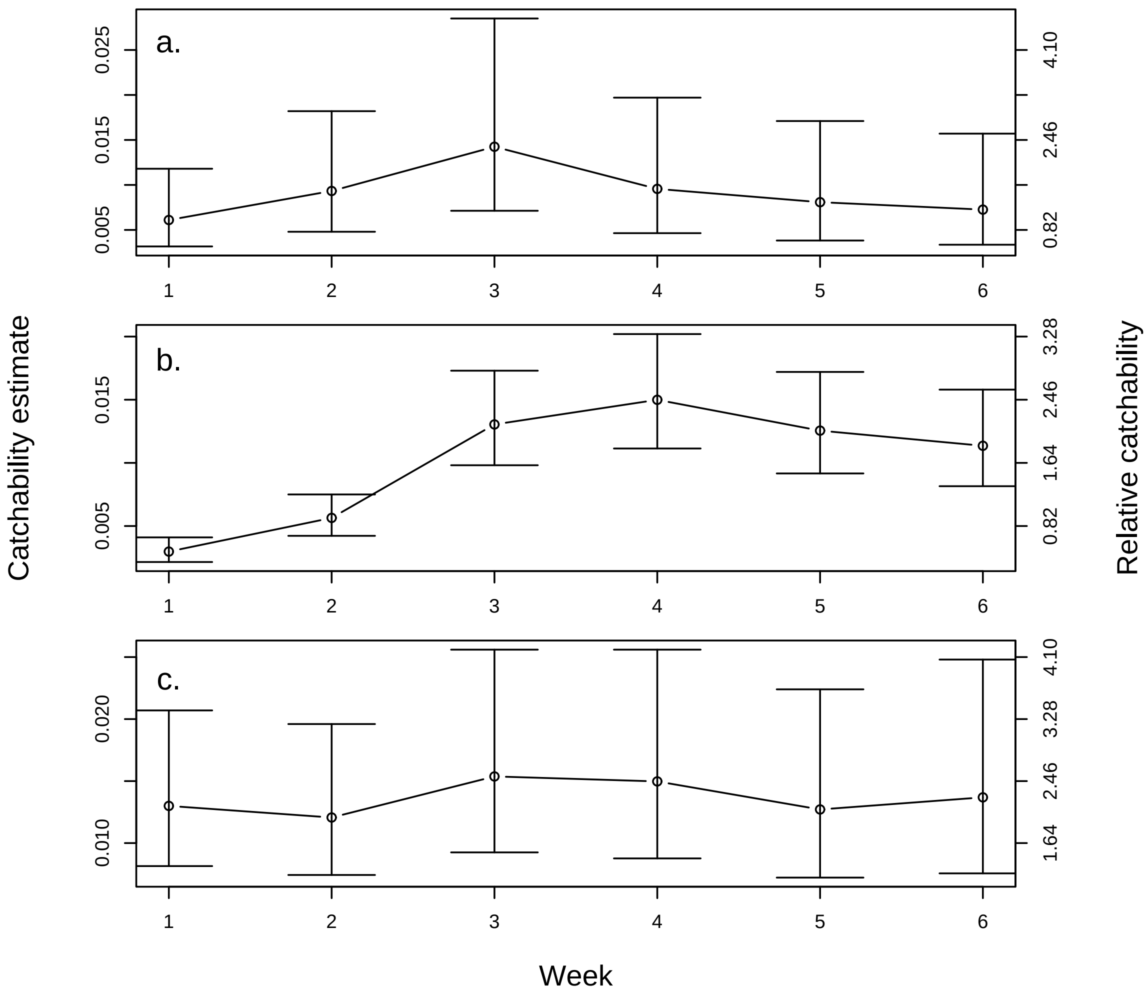


Figure 9: Estimates of weekly boundary troll catchability and approximate 95% confidence intervals for (a) Toboggan Creek, (b) Lachmach River, and (c) Babine River coho. Axes on the right show catchabilities relative to Tobbogan Creek for week 1.

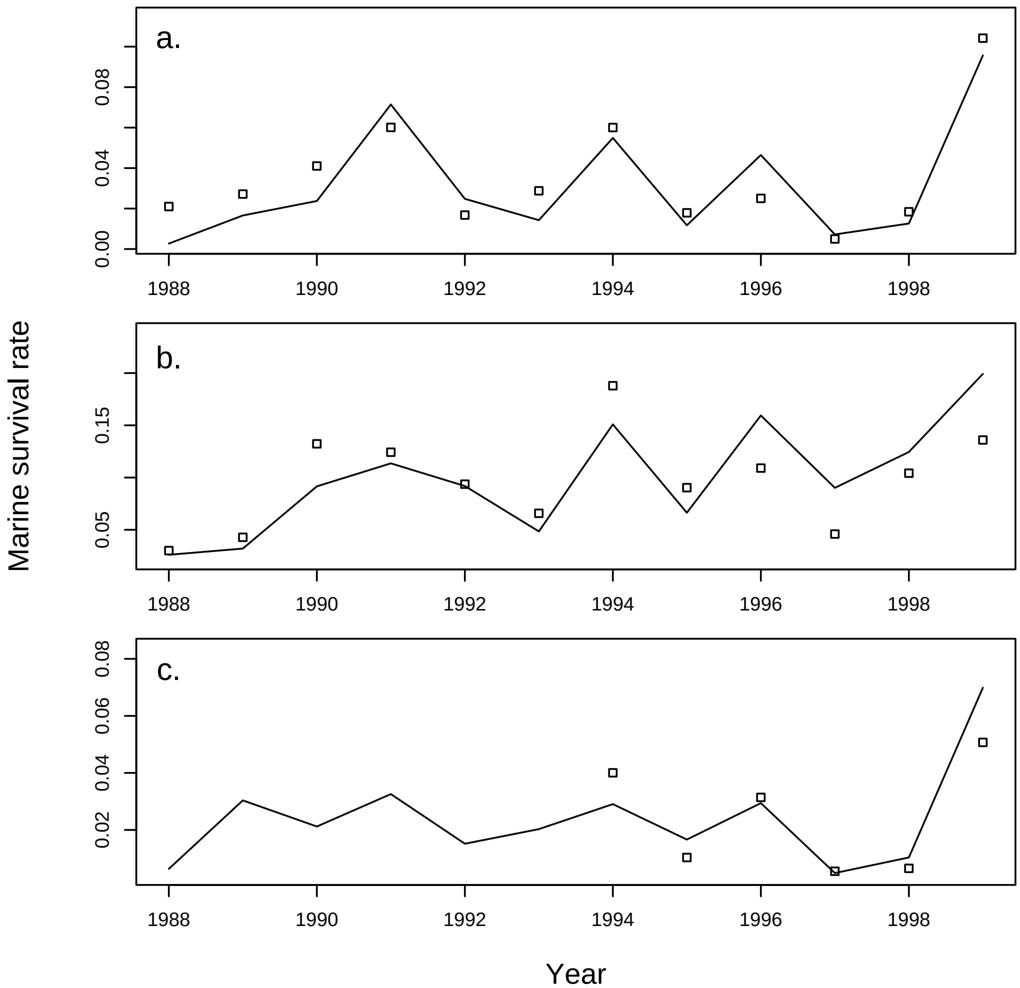


Figure 10: Observed (points) and estimated (lines) annual marine survival rates for (a.) Toboggan Creek, (b.) Lachmach River, and (c.) Babine River coho.

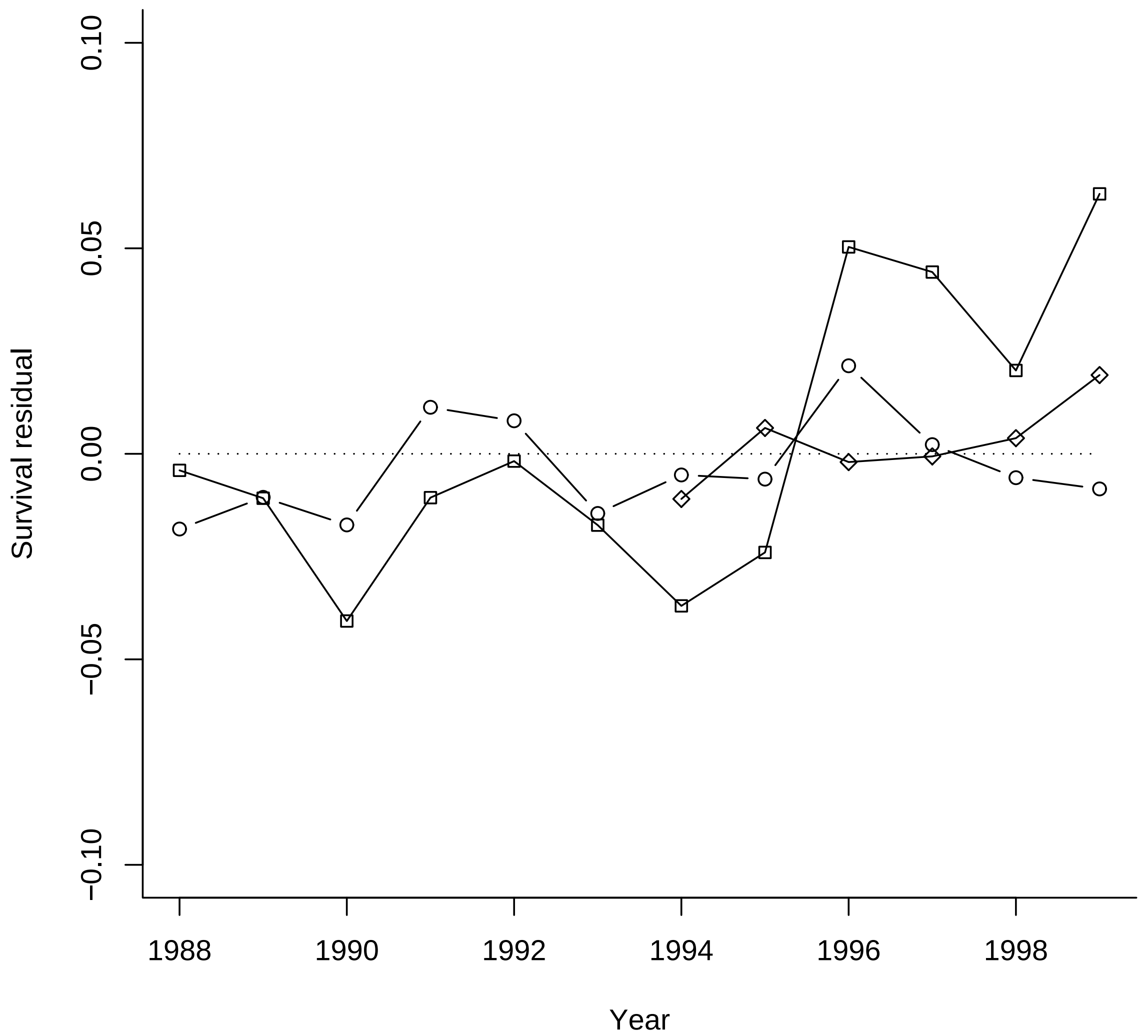


Figure 11: Residual deviations between in-season and post-season marine survival rate estimates for Toboggan Creek (circles), Lachmach River (squares), and Babine River (diamonds) coho.

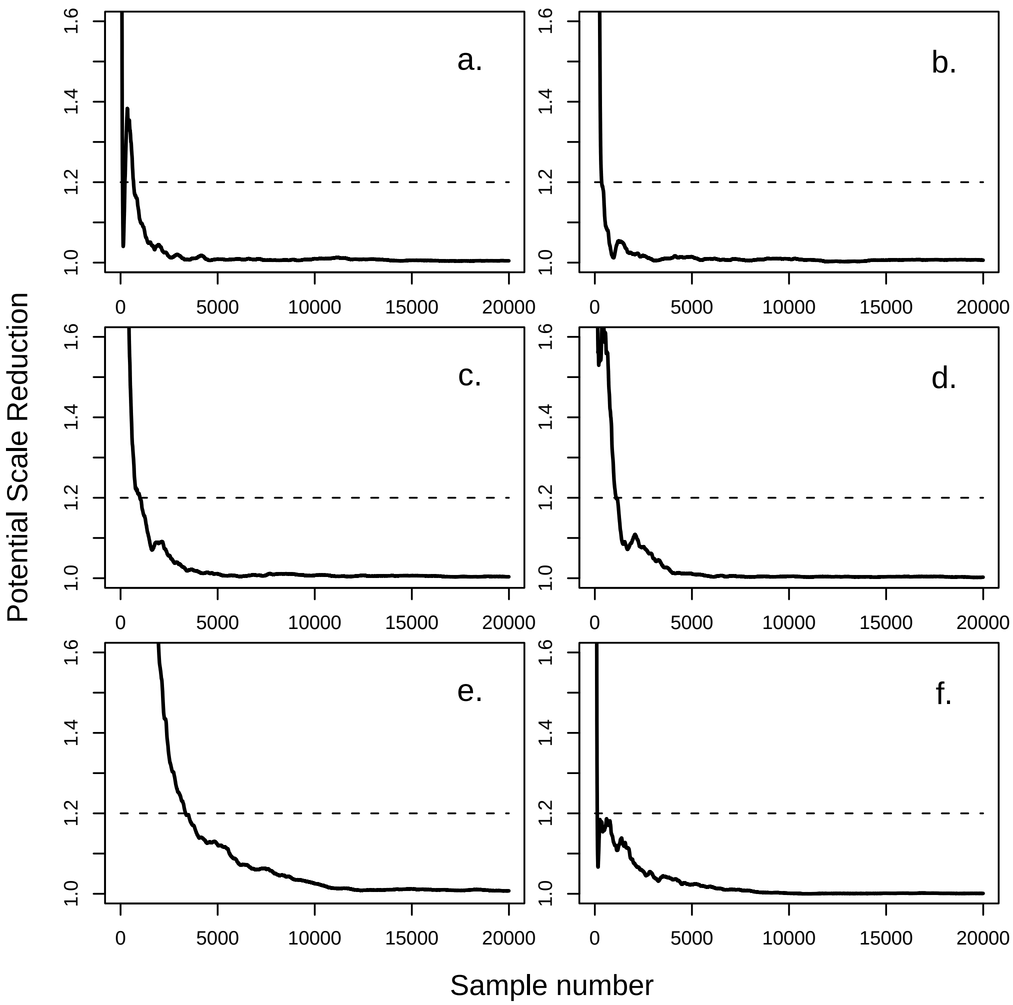


Figure 12: MCMC convergence statistics for catchability (left panels) and logit-survival rate (right panels) parameters for the sixth week of 1996. The MCMC algorithm is considered converged when the potential scale reduction $\Re \leq 1.2$ (dashed line). (a and b) Toboggan Creek, (c and d) Lachmach River, and (e and f) Babine River.

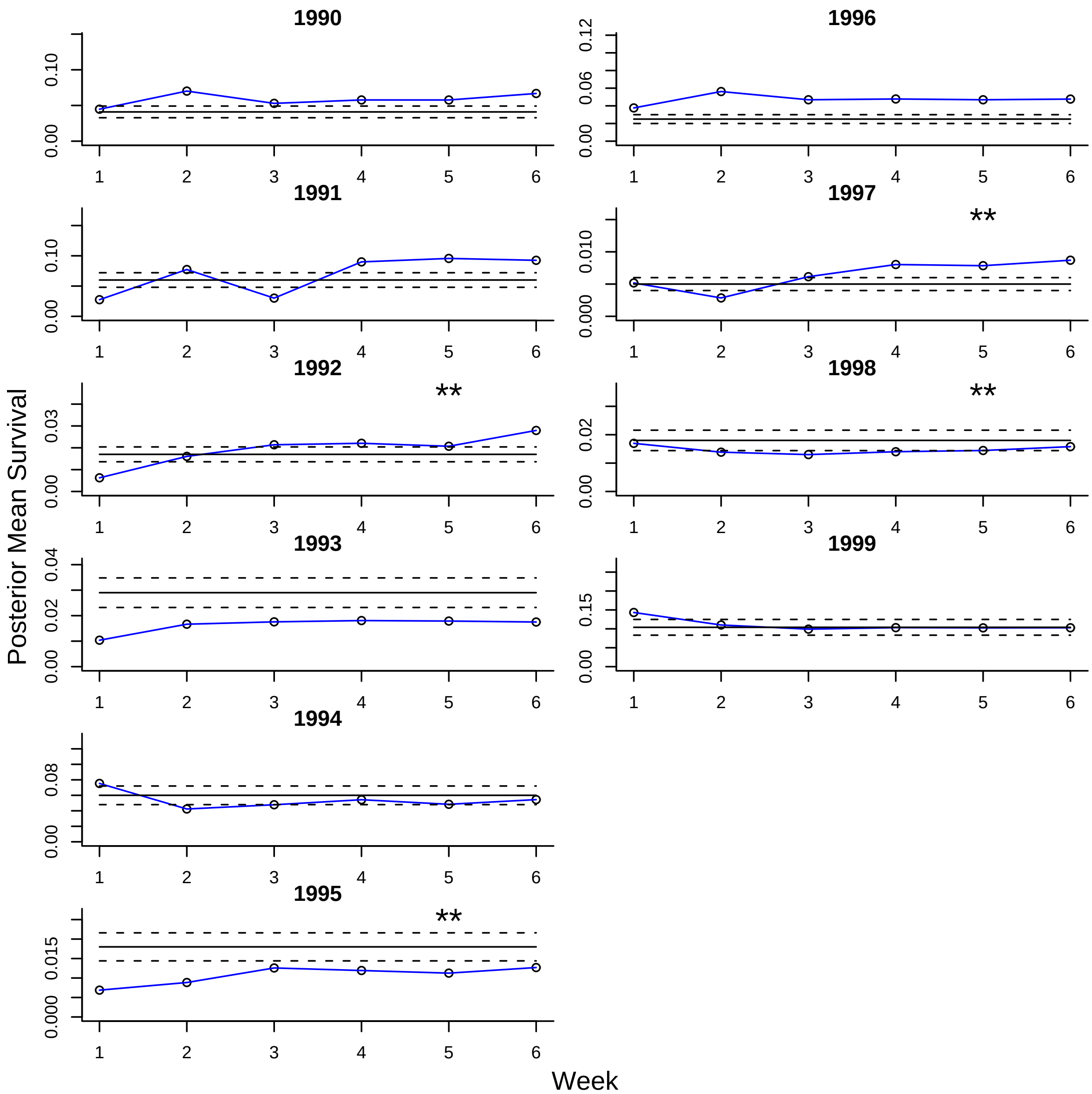


Figure 13: In-season performance of marine survival estimation scheme for Toboggan Creek coho. Circles connected by lines show the retrospective marine survival estimate based on data up to the week indicated. The solid horizontal line represents the post-season estimate and dashed lines are (±) 20% intervals. Double asterisks indicate years for which the post-season marine survival estimate is below the critical level.

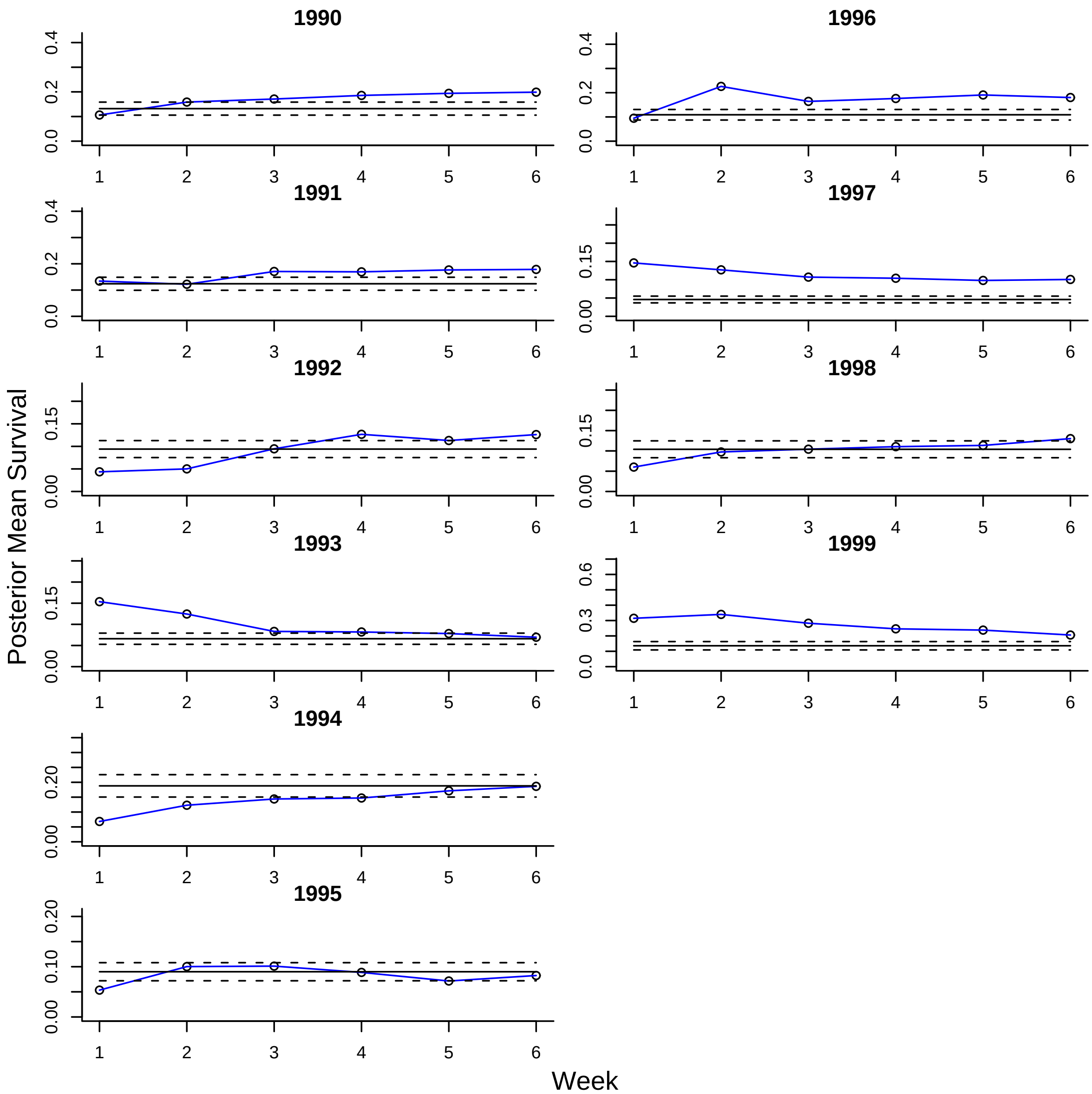


Figure 14: In-season performance of marine survival estimation scheme for Lachmach River coho. Circles connected by lines show the retrospective marine survival estimate based on data up to the week indicated. The solid horizontal line represents the post-season estimate and dashed lines are (±) 20% intervals. Double asterisks indicate years for which the post-season marine survival estimate is below the critical level.

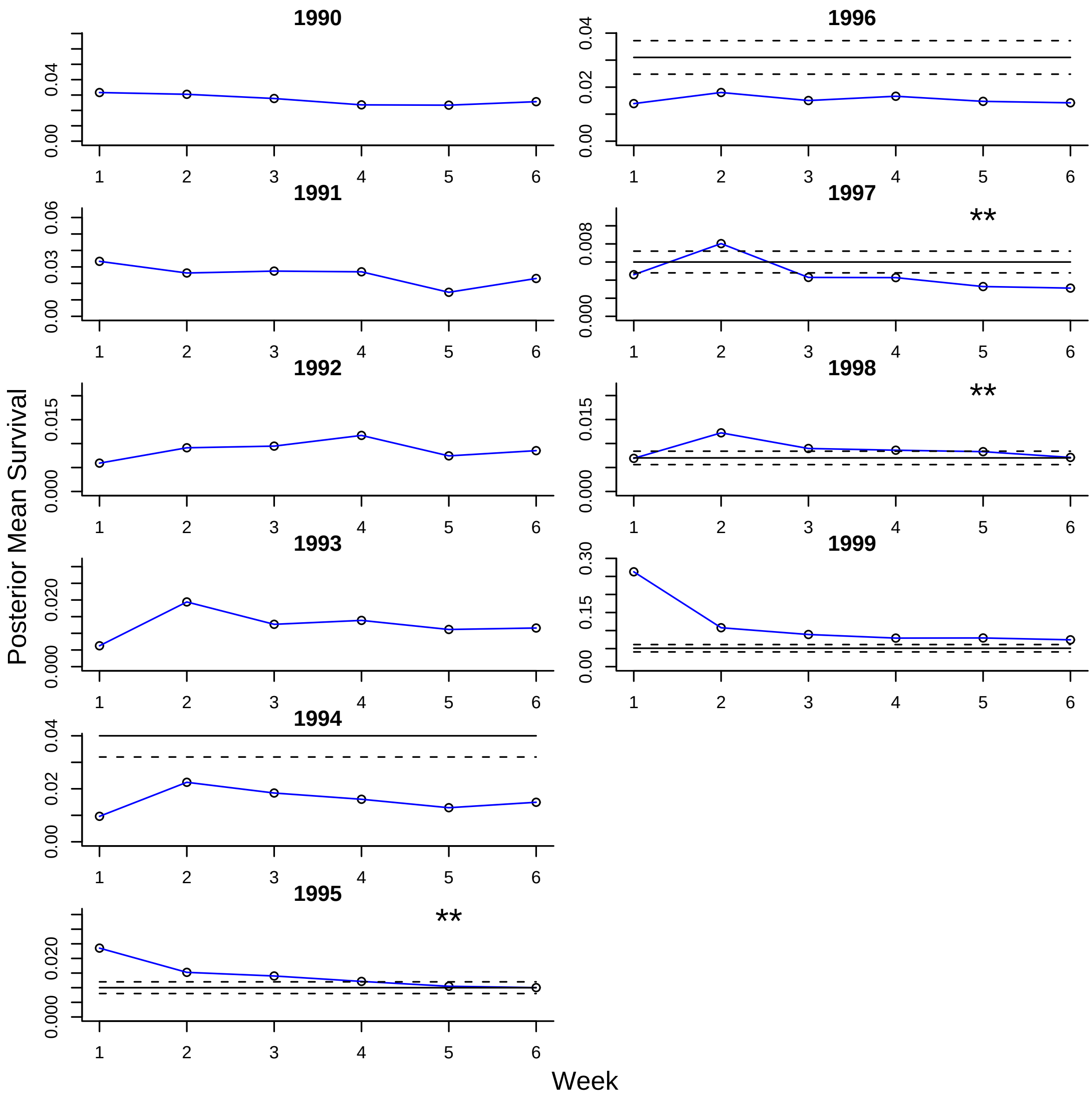


Figure 15: In-season performance of marine survival estimation scheme for Babine River coho. Circles connected by lines show the retrospective marine survival estimate based on data up to the week indicated. The solid horizontal line represents the post-season estimate and dashed lines are (±) 20% intervals. Double asterisks indicate years for which the post-season marine survival estimate is below the critical level.

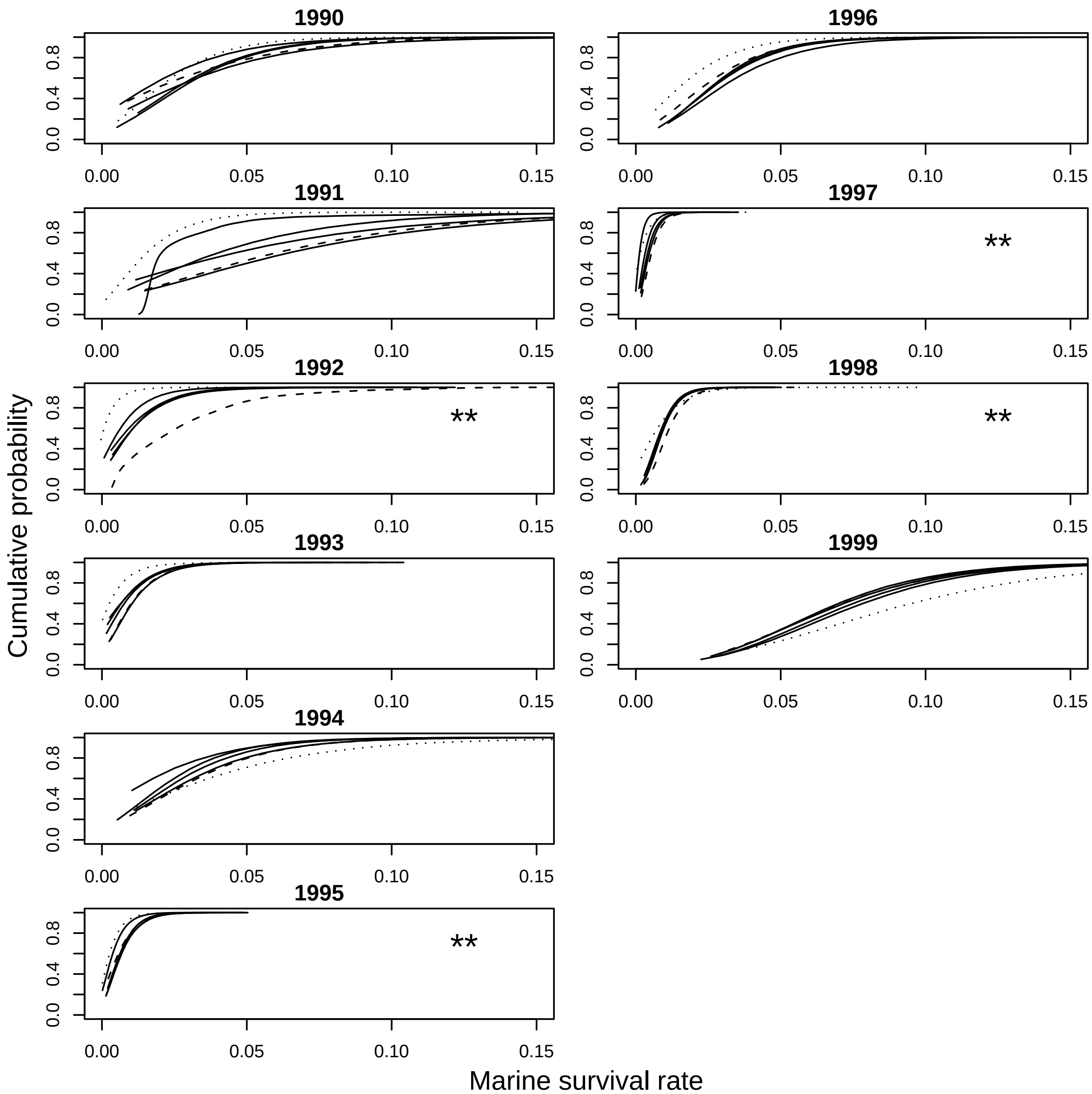


Figure 16: Weekly cumulative probability profiles for Toboggan Creek coho marine survival rate estimates. Dotted lines indicate results for the first week in each year, solid lines indicate intermediate weeks, and dashed lines show cumulative distributions for the last week. Double asterisks indicate years for which marine survival is below the critical level.

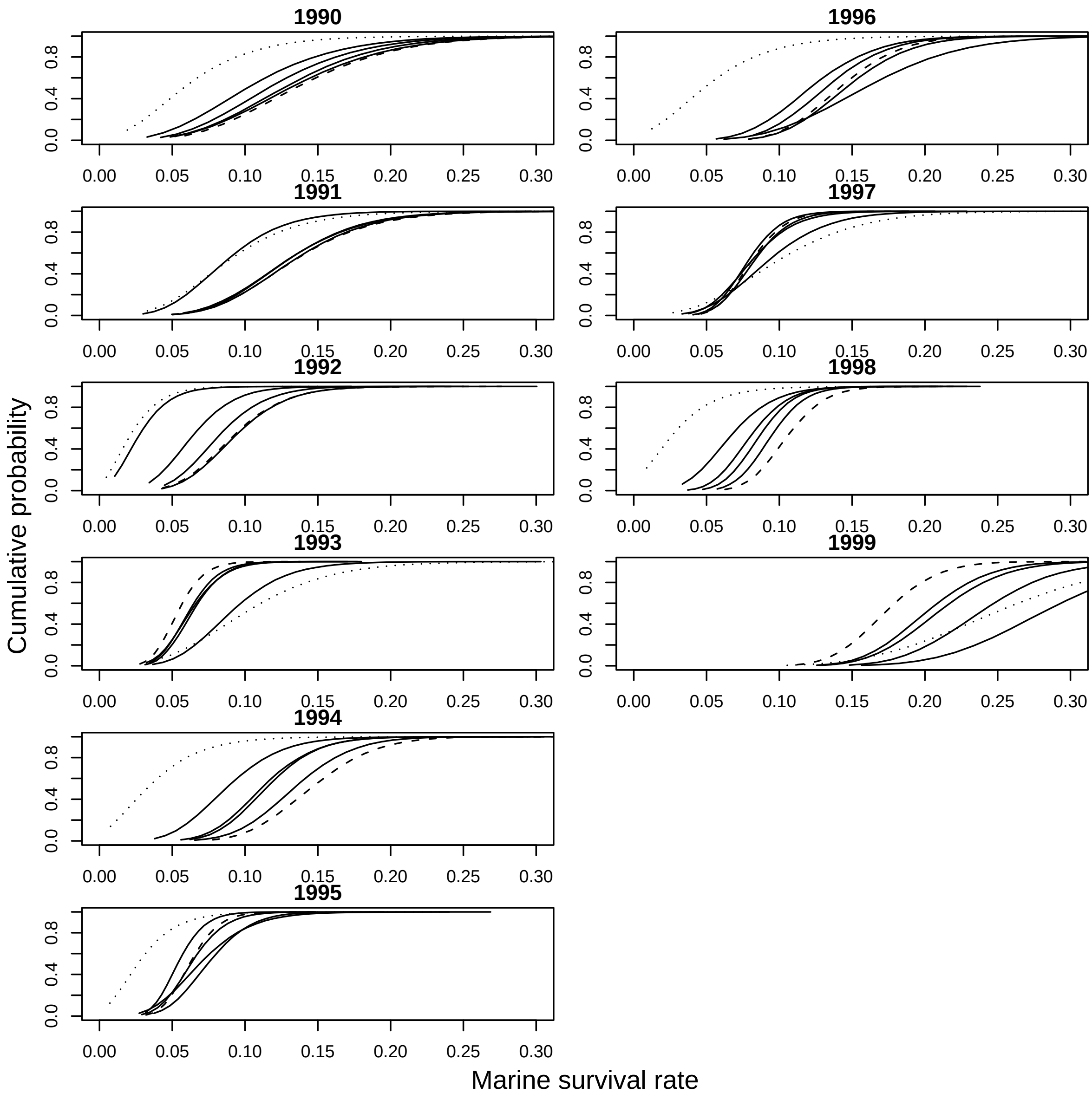


Figure 17: Weekly cumulative probability profiles Lachmach River coho marine survival. Dotted lines indicate results for the first week in each year, solid lines indicate intermediate weeks, and dashed lines show cumulative distributions for the last week. Double asterisks indicate years for which marine survival is below the critical level.

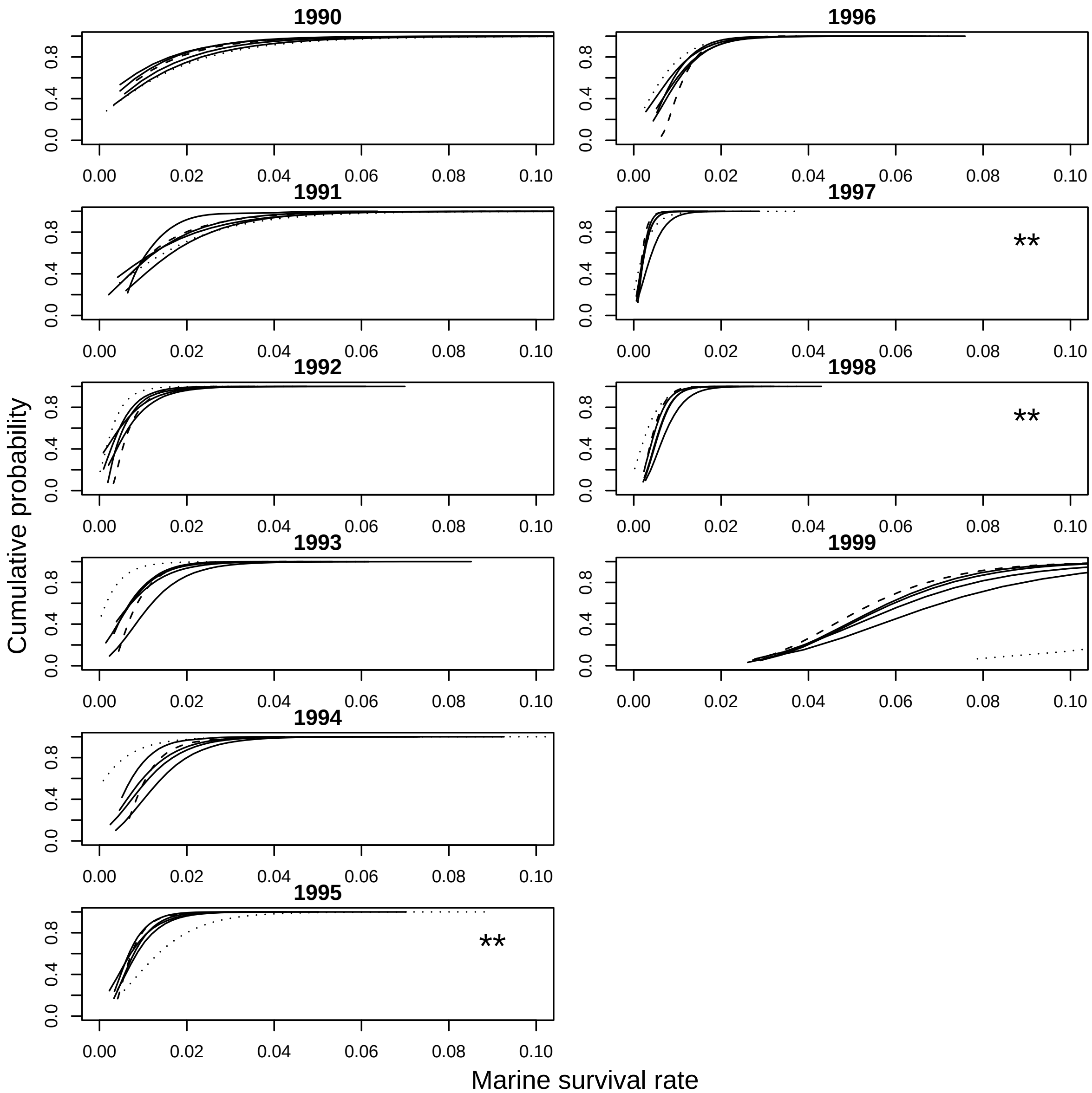


Figure 18: Weekly cumulative probability profiles Babine River coho marine survival. Dotted lines indicate results for the first week in each year, solid lines indicate intermediate weeks, and dashed lines show cumulative distributions for the last week. Double asterisks indicate years for which marine survival is below the critical level.

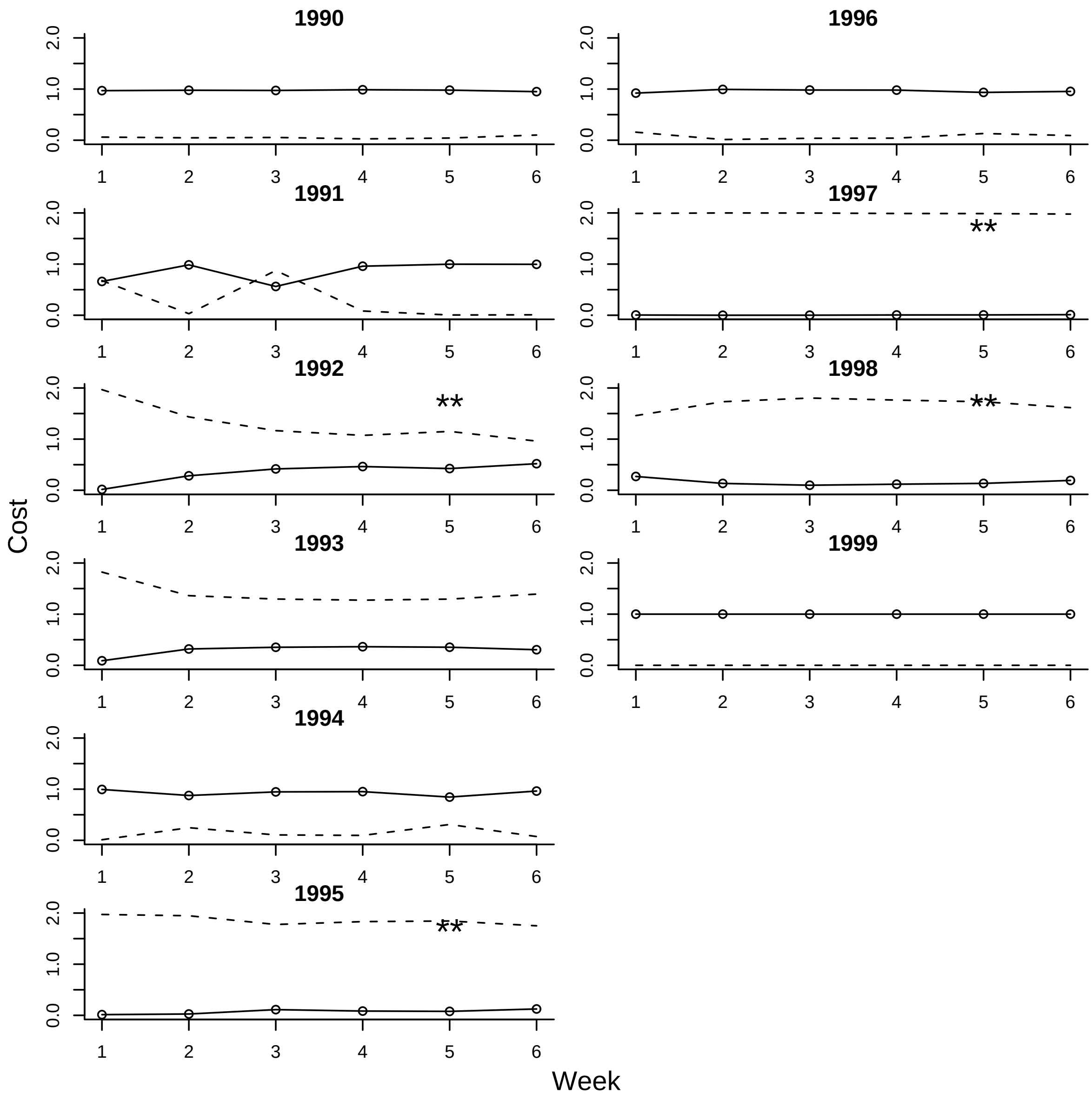


Figure 19: Results from the retrospective decision analysis for Toboggan Creek coho. Dashed lines show the expected cost of concluding that marine survival is greater than $S_{crit,j}$ based upon the data up to each week. Solid lines with circles show the expected cost of concluding that marine survival is less than or equal to $S_{crit,j}$. Double asterisks indicate years for which marine survival is below the critical level. A low marine survival forecast is issued when the dashed lines are above the solid lines.

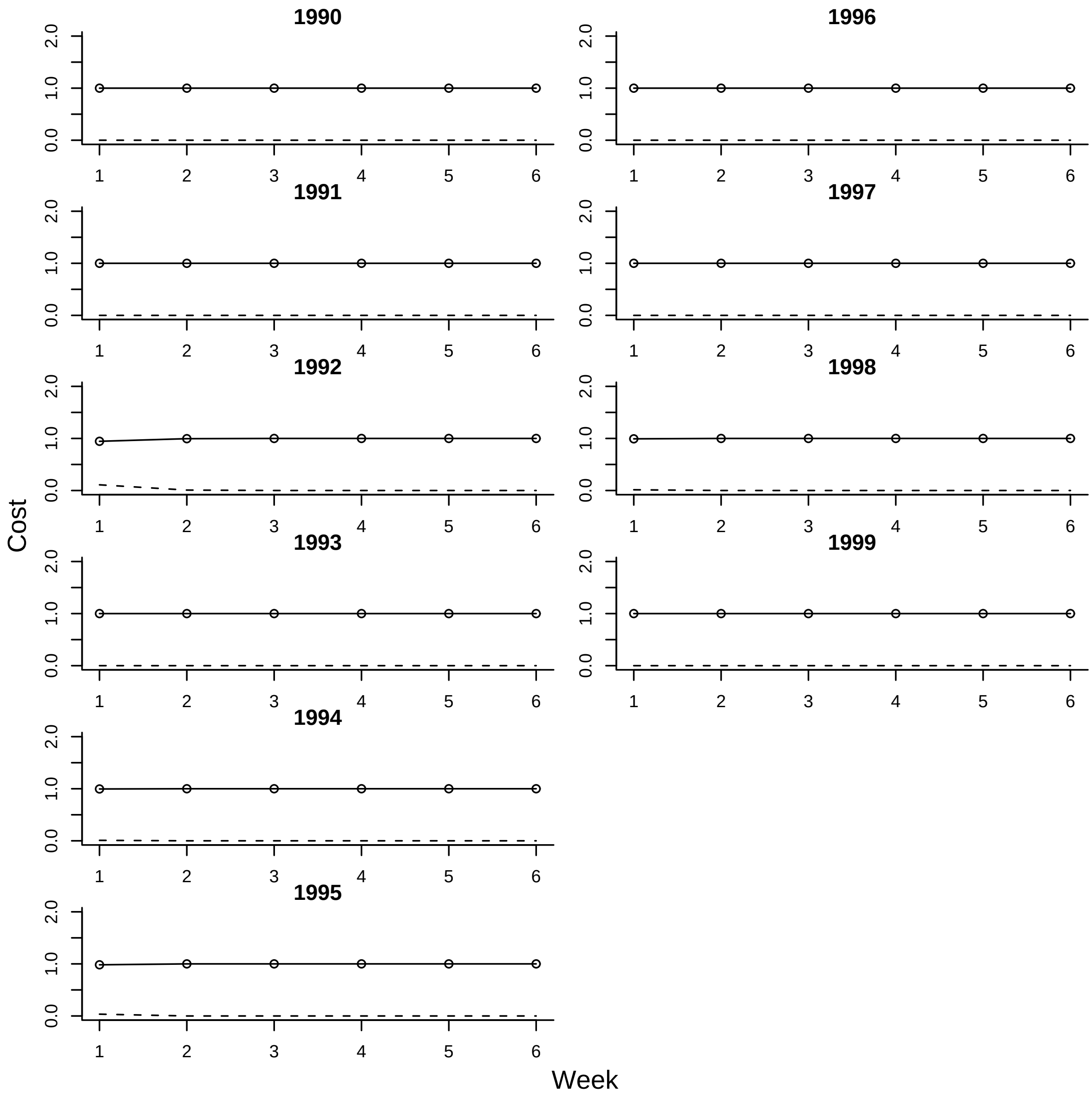


Figure 20: Results from the retrospective decision analysis for Lachmach River coho. Dashed lines show the expected cost of concluding that marine survival is greater than $S_{crit,j}$ based upon the data up to each week. Solid lines with circles show the expected cost of concluding that marine survival is less than or equal to $S_{crit,j}$. Double asterisks indicate years for which marine survival is below the critical level. A low marine survival forecast is issued when the dashed lines are above the solid lines.

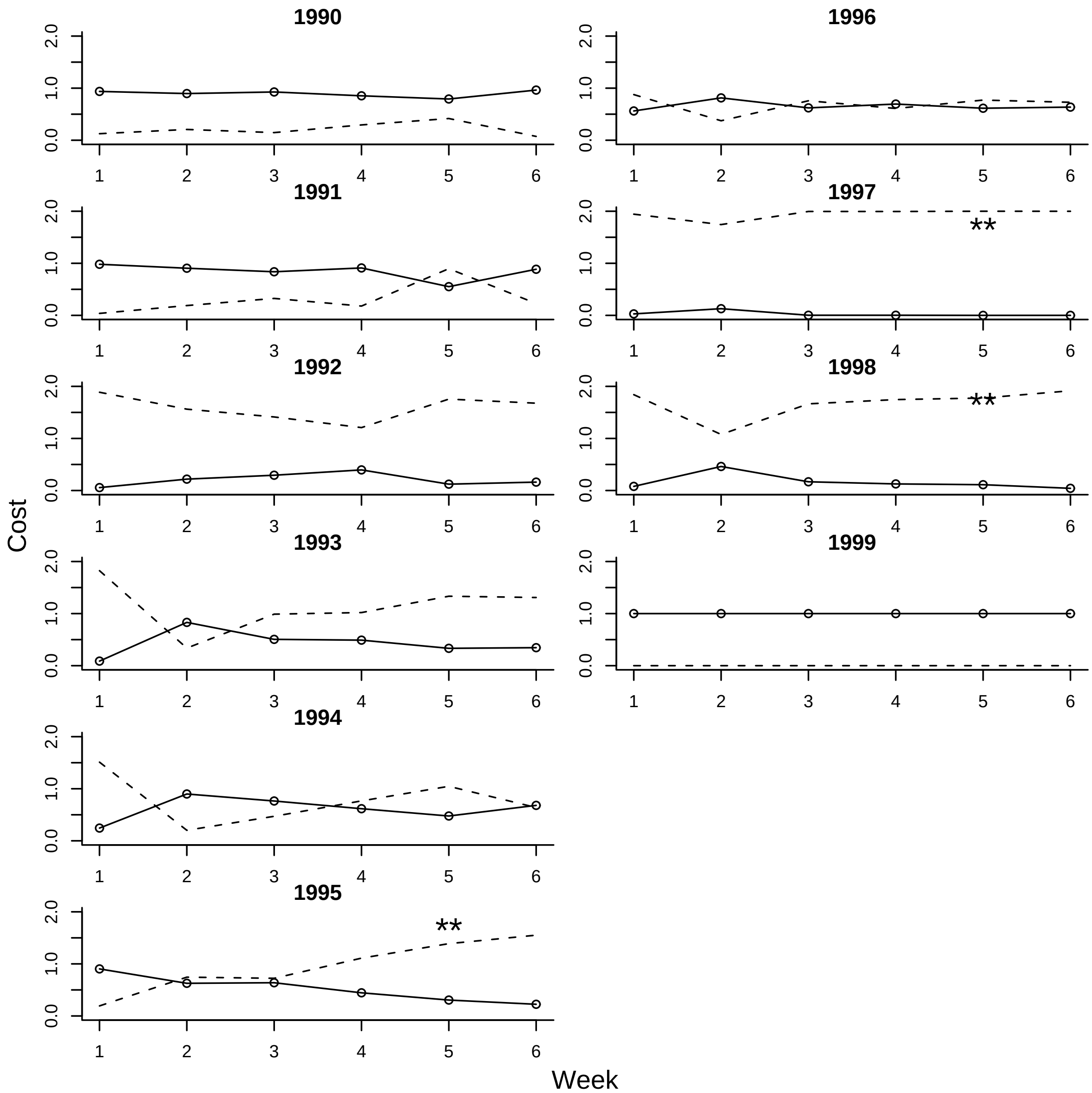


Figure 21: Results from the retrospective decision analysis for Babine River coho. Dashed lines show the expected cost of concluding that marine survival is greater than $S_{crit,j}$ based upon the data up to each week. Solid lines with circles show the expected cost of concluding that marine survival is less than or equal to $S_{crit,j}$. Double asterisks indicate years for which marine survival is below the critical level. A low marine survival forecast is issued when the dashed lines are above the solid lines.