Development of an in-season abundance assessment method for northern BC coho salmon to improve harvest advice

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Introduction

Coho salmon populations from northern BC pose several challenges for assessment and management. Their broad geographic distribution and tendency to spawn in small headwater streams makes escapement estimation difficult, while their occurrence in six mixed stock fisheries, both as directed and incidental catch, and in both the USA and Canada, makes it difficult to obtain stock-specific catch information. Historically, the average harvest rate for northern BC coho salmon has been approximately 60%, with about 45% of the return run being taken in Alaskan fisheries and the remaining 15% being taken in Canadian fisheries. Due to the occasional occurrence of extremely low marine survival rates and escapement levels throughout the 1990's (e.g., 1992, 1995, and 1997 return years), several northern BC coho populations, including populations from the Upper Skeena River, are considered to be of conservation concern.

Sustainable exploitation rates of coho salmon are strongly dependent upon smolt to adult survival rates in the marine environment (Bradford et al. 2000; hereafter referred to as "marine survival"). Although some Upper Skeena River coho stocks could sustain current exploitation levels on average, there is an important need to develop in-season forecasting procedures that provide an early-warning of extremely low marine survival rates. In-season marine survival rate forecasts need to be made available weeks in advance of Canadian coho fishery openings so that managers can take appropriate actions to prevent over-harvesting (Holtby et al. 1999).

Historically, preseason forecasts of marine survival for northern BC coho had been generated using time-series and sibling analysis (Sawada et al. 2003); however, these forecasting methods have performed very poorly in the past due to high interannual variation in freshwater and marine survival rates. As a result, preseason forecasts for northern coho are no longer attempted (Joel Sawada, Fisheries and Oceans Canada [DFO], North Coast Stock Assessment Division, Prince Rupert, BC, pers. comm.). Although post-season estimates of marine survival are available for certain indicator streams, the long lag time between fishery interception and escapement enumeration, which occurs hundreds of kilometers upstream, precludes the use of these estimates for in-season management decisions.

In light of the above challenges, initial efforts have been taken to develop in-season marine survival forecasting methods and in-season management frameworks for northern BC coho salmon. Holtby (2000) examined the utility of four possible in-season indictors of northern BC coho run-strength and marine survival using correlation tests. For multiple combinations of in-season indictor and week, he tested the predictive strength of the indictor, as well as the number of years in the historic time series that the predictive relationship would have i.) correctly detected marine survival to be below a pre-determined threshold and ii.) incorrectly detected marine survival to be below a pre-determined threshold within two different confidence intervals (80% and 50%). Two drawbacks of this method include that it requires the selection of an appropriate p-value to determine whether an observed relationship is significant, and that it does not provide a means to explicitly include uncertainty in marine survival estimates into the provision of management advice. Cox et al. (2003) attempted to improve this procedure in two ways. First, they modeled coded-wire tag returns as a function of the number of CWT coho released each year, annual marine survival rates, and Alaskan border troll fishing effort in the year of return. A key feature of this modeling approach is that post-season estimates of marine survival were used to provide an informative prior distribution for marine survival rates. Second, the resulting posterior distributions for marine survival rates were used in a formal Bayesian decision analysis to calculate the costs, or risks, associated with two possible conclusions about marine survival; that is, whether marine survival was greater or less than a pre-determined threshold. A 10-year retrospective analysis demonstrated that this procedure was reasonably reliable at providing correct poor marine survival warnings when needed, while at the same time avoiding false detections that would unnecessarily reduce harvest.

This paper extends the Cox et al. (2003) methodology to evaluate several additional indicators that may further improve in-season forecasts of coho salmon marine survival rates. Indicators included weekly total coho catch data from the Alaskan troll fishery aggregated over multiple stocks, the Tree Point gillnet test fishery catch-per-unit-effort (CPUE), total catch in the southeast Alaskan pink salmon fishery, and CPUE in two coho sport fisheries off Haida Gwaii. We combine these candidate indicators with the CWT model developed by Cox et al. (2003) using Bayesian methods to forecast marine survival for the Toboggan Creek hatchery stock. We focus our analysis on the Toboggan Creek hatchery stock because it is the only remaining coho indicator stock in the Skeena or Nass Watersheds. We use a retrospective analysis to determine which combinations of aggregate catch and CWT data improve forecasting and management performance over the CWT model alone.

We expanded on the methodology developed by Cox et al. (2003) in three ways in addition to incorporating aggregate catch indices into the forecasting procedure. First, our analysis uses troll fishing effort data for the boundary area fishery that is available in-season from aerial overflights, as opposed to the post-season estimates of fishing effort that were used by Cox et al. (2003). In-season effort provides a more realistic measure of forecasting and management performance for the CWT model because this is the level of information that would be available in-season. Second, the prior distribution on marine survival was based only on historical data up to the year of the forecast. In contrast, Cox et al. (2003) used a prior distribution that was based on the complete dataset. Finally, we added six additional years of data to the retrospective analysis.

Methods

Data sources

Post-season estimates of marine survival for the Toboggan Creek indicator stock were provided by Fisheries and Oceans Canada (Table 1; Joel Sawada, DFO, North Coast Stock Assessment Division, Prince Rupert, BC, pers. comm.). We transformed marine survival rates to the logit scale for the non-linear estimation procedures described below.

Data on historical CWT releases for Toboggan Creek coho salmon and corresponding recoveries from the boundary area troll fishery were obtained from the Regional Mark Information System online database (RMPC 2006; Table 1). Data on weekly total coho catch (pieces) and effort (boat days) for the troll fishery were provided by Alaska Department of Fish and Game (Tables 2 and 3; Leon Shaul, Alaska Department of Fish and Game [ADFG], Commercial Fisheries Division, Douglas, Alaska, pers. comm.). Troll fishery effort data was collected in-season using aerial overflights. Weekly coho catch and effort data for the Alaskan gillnet fishery at Tree Point and annual total pink salmon catch from southeast Alaska, which occurs prior to the opening of the Canadian coho fishery, were also provided by ADFG (Tables 4 and 5; Leon Shaul, ADFG, Commercial Fisheries Division, Douglas, Alaska, pers. comm.). Data for the gillnet fishery at Tree Point were summarized as cumulative weekly CPUE for combined hatchery and wild coho catch. Average monthly CPUE data (June and July) for two coho salmon sport fisheries in Haida Gwaii, BC (Areas 1 and 2) were provided by DFO (Table 6; Joel Sawada, DFO, North Coast Stock Assessment Division, Prince Rupert, BC, pers. comm.). While Haida Gwaii sport fishery data is available for 1996 onwards, we excluded data from 1998-1999 and 2002 from the analysis because management actions during these years may have affected the index (Joel Sawada, DFO, North Coast Stock Assessment Division, Prince Rupert, BC, pers. comm.).

In-season CWT catch model

We used the coded-wire tag model developed by Cox et al. (2003) to predict abundance and catch of CWT coho for each year and week of the boundary troll fishery as a function of the number of CWTs initially released, marine survival for each return year, and troll fishing effort for each week and year. Using this model, the predicted CWT catch for year *t* and week *w* is

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

where q_w is week-specific troll fishery catchability, $E_{t,w}$ is an in-season estimate of fishing effort for week *w* in year *t*, and $N_{t,w}$ is the predicted number of CWT coho available to the fishery in week *w* of year *t*. The number of CWT coho available to the fishery is assumed to follow the survival-depletion model

(2) $$N_{t,w} = s_t R_t - \sum_{j=27}^{w-1} \hat{C}_{t,j} \ .$$

where s_t and R_t are the average marine survival rate and number of coded-wire tagged fish released from Toboggan Creek for retrun in year *t*.

The total parameter set estimated by the CWT model (Θ_{CWT}) included six weekly troll fishery catchabilities, q_j (j = 27, 28, … 32; assumed constant over all years), and annual marine survival, s_x (x = 1991, 1992, … t),

(3) $$\Theta_{\mathrm{CWT}} = \left(\left\{ q_j \right\}_{j=27}^{w} \left\{ s_x \right\}_{x=1991}^{t} \right).$$

We assumed that the weekly CWT catches followed a Poisson distribution when fitting equations 1-2 to observed CWT catches. Therefore, the negative log-likelihood function is (ignoring additive constants that depend only on the data)

(4) $$\ell_{\mathrm{CWT}} \left(\mathrm{C} \middle| \Theta_{\mathrm{CWT}} \right) = \sum_{x=1991}^{t} \sum_{j=27}^{w} \hat{C}_{x,j} - C_{x,j} \log_e \left(\hat{C}_{x,j} \right),$$

where **C** represents the matrix of observed CWT catches up to week *w* of year *t* and the predicted catches $\hat{C}_{x,j}$ depend on parameters Θ_{CWT} according to equations 1-2.

In-season aggregate catch model

We developed and tested 31 combinations of aggregate catch and CWT forecasting models to determine whether including more in-season information would improve marine survival rate forecasts compared to that of the CWT model alone. Each aggregate model generated a predicted catch index *Y* as a function of marine survival and two forecast parameters. Combining these aggregate catch models with the CWT model allowed us to compute the joint likelihood of the CWT and catch index data given a marine survival rate that was common to both models. Other parameters such as CWT model catchabilities and aggregate catch forecast parameters were specific to the individual models. These model-specific parameters are assumed constant among years.

Catch indices in year *t* were modeled as a function of marine survival by the following power function

(5) $$\hat{Y}_{i,t,w} = \alpha_{i,w} s_t^{\beta_{i,w}+\varepsilon_{i,t,w}},$$

where, $\hat{Y}_{i,t,w}$ is the predicted catch value for index *i* in week *w* of year *t*, s_t is the marine survival rate used in the CWT model for year *t* (i.e., same as in equation 2), $\alpha_{i,w}$ and $\beta_{i,w}$ are index- and week-specific forecast parameters and the error $\varepsilon_{i,t,w} \sim N\left(0,\sigma_{i,w}^2\right)$. The regression coefficient β expresses the degree of curvature in the relationship between marine survival *s* and the in-season index *Y*. This parameter was added to the models after exploratory analyses revealed that many indices appeared to be non-linearly related to marine survival rates. In cases where the data do not support a non-linear hypothesis, the estimate of β will be close to 1 (i.e., linear).

For each year t, forecast parameters $\alpha_{i,w}$, $\beta_{i,w}$, and $\sigma_{i,w}$ were assumed known; that is, they were not treated as free parameters to be estimated along with marine survival in a given year. Values for these parameters were estimated by a simple linear regression of aggregate catch data on post-season estimates of marine survival for all years prior to t. The regression equation, after log-transformation and ignoring subscripts, is

(6) $$\log_e(Y) = \log_e(\alpha) + \beta \log_e(s) + \varepsilon$$

Aggregate catch model likelihood

Equation 6 generates a forecast of $\log_e(\hat{Y}_{i,t,w})$ (setting the error equal to 0) for an in-season index given the forecast parameters and a value for marine survival in year t. We then computed the negative log-likelihood function for the observed index $\log_e(Y_{i,t,w})$

(7) $$\ell_{\mathrm{AGG}}\left(\log_e(Y_{i,t,w}) \mid \log_e(\hat{Y}_{i,t,w})\right) \propto \frac{\left(\log_e(Y_{i,t,w}) - \log_e(\hat{Y}_{i,t,w})\right)^2}{2\sigma_{i,w}^2}$$

where we dropped additive constants that do not depend on the unknown parameter s_t. This negative log-likelihood follows from our the assumption in equation 6 that errors in $\log_e(Y)$ are normally distributed. The only unknown parameter in the in-season aggregate catch model was marine survival in the current year, s_t,

(8) $$\Theta_{Agg} = s_t .$$

Posterior distribution for marine survival rate forecast

We are interested in forecasting the marine survival rate in year *t* along with the uncertainty in that forecast given all the available data (i.e., CWT and aggregrate indices). Therefore, we must compute the marginal posterior probability distribution for the marine survival rate forecast, which can be done by integrating (e.g., taking the sum) the joint posterior distribution over all uncertain model parameters except marine survival. This joint posterior distribution is a combination of the likelihoods of the observed data given marine survival and the prior distribution for marine survival. The negative-logarithm of the joint posterior is therefore,

(9)

$$\log_e \ell\left(s_t, Q_w \middle| C_{t,w}, Y\right) = \ell_{\mathrm{AGG}}\left(\log_e(Y_{i,t,w}) \,|\, \log_e(\hat{Y}_{i,t,w})\right) + \ell_{\mathrm{CWT}}\left(\mathbf{C} \,|\, \Theta_{\mathrm{CWT}}\right) + \frac{\left(\mathrm{logit}(s_t) - \mu_{s,t-}\right)^2}{2\sigma^2_{s,t-}}$$

where $\mathrm{logit}\left(s_t\right) = \log\left(\frac{s_t}{1-s_t}\right)$ and $\mu_{s,t-}$ and $\sigma_{s,t-}$ are the prior mean and standard deviation of logit-transformed marine survival. The *t*- in the last term indicates that the prior mean and standard deviation are based on data for years *prior* to *t*.

Computing the marginal posterior distribution for any marine survival rate forecast must be accomplished numerically because of the complicated nature of the posterior in equation 9. Therefore, the joint posterior distribution was generated using a two-step procedure in which a Quasi-Newton routine first minimized the negative log-posterior in equation 9. This procedure generated maximum posterior density (MPD) estimates for all estimated parameters, which we then used as starting points for a Markov Chain Monte Carlo (MCMC) simulation (Gelman et al. 2004). The MCMC procedure is intended to generate a random sample from the multi-dimensional posterior from which we can then easily generate the marginal posterior distribution for marine survival alone. Initial iterations of the MCMC procedure showed that the acceptance rate of simulations was low. Reducing the scale of the jumping distribution to 0.35 achieved acceptance rates ranging from 0.38 to 0.55. We ran 50 000 MCMC iterations and sampled every 125th value to avoid autocorrelation (Appendix 1). The first 25 000 samples were discarded for burn-in, resulting in a total of 200 posterior sample points that were used to make inferences about parameter values.

In-season management procedure

The end-product of the MCMC procedure is a Bayesian marginal posterior distribution describing the probability associated with different marine survival values for year t. This information can be used in many ways for making in-season decisions that account for uncertainty in the models and data. In this section, we demonstrate a decision-analytic approach to making in-season management decisions about coho fisheries. We consider two alternative possibilities, or states of nature, regarding annual marine survival in our decision analysis. The first state is that marine survival for the current year, s_t, is less than or equal to the critical value required to open the Canadian fishery, s^*, while the second state is that s_t is greater than the critical value. We used the forecasted posterior distribution of s_t to assign probabilities to the two alternative states of nature. The probability $p_{t,w}$ assigned to the first state of nature, $s_t \leq s^*$, was the proportion of the marginal posterior distribution estimated in week w of year t that fell on or below s^*, while the probability assigned to the second state of nature, $s_t > s^*$, was simply $1 - p_{t,w}$. We assigned these probabilities to the two elements of a vector $\mathbf{P}_{t,w}$. For our analysis, we used an s^* value of 0.02, which is the same value used by Holtby 2000 to identify years with undesirably low marine survival rates for Toboggan Creek coho. This value represents 20% of the observed mean marine survival rate prior to 2000, and is larger than marine survival rates seen for 1992, 1995, 1997, and 1998 return years, which were all considered undesirably low marine survival years for coho (Holtby 2000).

We used a simple decision matrix, **D** (Table 7), to characterize the implied costs, or risks, that managers in our hypothetical management scenario could expect from Type I and II errors relative to each other. When the true state of nature matches the conclusion made by the fisheries manager, then the cost of the decision to open or not open the fishery is zero. When the true state of nature is $s_t > s^*$ but the manager incorrectly concludes that $s_t \leq s^*$ and does not open the fishery, a Type I error is committed and the associated cost is 1. Conversely, when the true state of nature is $s_t \leq s^*$ but the manager incorrectly concludes $s_t > s^*$ and opens the fishery, a Type II error is committed and the associated cost is 2. In other words, in our hypothetical management scenario, the cost of making a Type II error is twice as high as that of a Type I error. It should be noted that the values assigned to each error type in **D** are only meaningful relative to each other. The vector of expected costs associated with each decision was computed as $\mathbf{U}_{t,w} = \mathbf{D}\mathbf{P}_{t,w}$. Given that the primary management goal in our hypothetical scenario is to minimize expected cost, the optimal decision to be made by a fisheries manager in week w of year t is the one corresponding to the smallest element in $\mathbf{U}_{t,w}$.

As an example of how this decision analysis works, assume that in week w of year t it is estimated that there is a 20% chance that $s_t \leq s^*$ and a 80% chance that $s_t > s^*$. The expected cost of concluding that marine survival is less than or equal to the critical rate is therefore (0)(0.2)+(1)(0.8) = 0.8, while the expected cost of concluding that marine survival is greater than the critical rate is (2)(0.2) + (0)(0.8) = 0.4. These two values represent the elements in the cost matrix $\mathbf{U}_{t,w.}$ A rational manager in our hypothetical scenario would decide to open the fishery due to the lower expected cost associated with concluding that $s_t > s^*$.

Retrospective analysis

We used retrospective analyses to compare forecasting and management performance of the 32 candidate models considered (31 aggregate catch models and the CWT model on its own). The time series for retrospective analyses extended over 18 years (1988-2005) with six weeks of in-season catch data available in each year (statistical weeks 27 to 32, where statistical week 27 is approximately the last week of June or the first week of July). The first three years of data were used to initialize the forecasting procedure, making year t = 1991 the first year included in the retrospective analysis. For each week w and year t in the retrospective time series (w = 27, 28,…32; t = 1991, 1992, …, 2005), model estimates and management advice on whether to open the fishery were made for year t using only data that would have been available to managers in week w of year t. For years prior to year t, data from all weeks were used, while for year t, only data up to week w were used. We conducted a total of 32 retrospective analyses; one for each of the candidate models.

We used four different measures to compare the relative performance of the 32 models. Mean absolute error (MAE), mean relative error (MRE), and root mean square error (RMSE), which are all commonly used to describe model fit (e.g., Punt et al. 2002, Haeseker et al. 2005), characterize the differences between in-season forecasts of marine survival, $\hat{s}_t$, and observed post-season estimates, s_t. MAE represents the average marine survival forecast bias over *n* years, i.e.,

$$\text{(10)} \qquad \text{MAE} = \frac{1}{n}\sum_{t=1991}^{t=2005}\left|\hat{s}_t - s_t\right|$$

MAE values are restricted to ≥ 0, and thus, MAE = 0 indicates a perfect model fit in all years. MRE characterizes the average marine survival forecast bias as a proportion of the observed post-season estimate, i.e.,

$$\text{(11)} \qquad \text{MRE} = \frac{1}{n}\sum_{t=1991}^{t=2005}\frac{\left|\hat{s}_t - s_t\right|}{s_t}$$

and thus, assigns equal weight to errors made in years with high and low s_t. The third measure of model fit, RMSE, characterizes the precision of annual forecasts, i.e.,

$$\text{(12)} \qquad \text{RMSE} = \sqrt{\frac{\sum_{t=1991}^{t=2005}\left(\hat{s}_t - s_t\right)^2}{n}}.$$

Models with smaller RMSE values will produce annual forecasts with narrower confidence intervals.

The fourth performance measure was the average management cost over all years in the time series, calculated using relative cost values of 1 and 2 for Type I and Type II errors, respectively. These are the same costs involved in the decision analysis (Table 7). Average management cost was calculated as

$$\text{(13)} \qquad \text{Cost} = \frac{1}{n}\left(k_1 + 2k_2\right),$$

where k_1 and k_2 represent the number of Type I and II errors, respectively, made over n years in the retrospective analysis. For all four performance measures, n was smaller for model combinations that included CPUE from either of the two sport fisheries (S1 and S2) because only seven years of sport fishery data were available. Excluding the first three years from comparisons (to allow for model initialization), n = 4 for model designs using sport fishery data and n=14 for all other designs.

Convergence diagnostics

We assessed convergence of the MCMC algorithm by visual inspection of four independent Markov chains and by computing a potential scale reduction factor (Gelman et al. 2004). The potential scale reduction method uses an analysis of variance to compare the variance among independent MCMC chains to the variance within each chain. Chains are made independent by initiating each at a different (over-dispersed) starting point. The staring parameter values for each chain were 1, 2, -1, and -2 standard deviation units away from the mean value for each parameter. Means and standard deviations for each parameter were calculated from the posterior distribution produced by an initial run of the MCMC procedure with starting parameter values set equal to those obtained from the Quasi-Newton optimization.

Approximate convergence is said to be achieved when the stationary distribution of each chain is similar to the stationary distribution of all chains combined. The statistic, $\Re$, represents the potential reduction in the scale (i.e., variance) of the posterior distribution that would occur if the sampling continued indefinitely. Ideally, the target $\Re$ should be 1.0; however, $\Re \leq 1.1$ is generally considered acceptable for indicating approximate convergence (Gelman et al. 2004). Convergence diagnostics were computed for all combinations of week and year for the CWT model, and on a subset of CWT-aggregate catch model combinations (Appendix 2). The large number MCMC procedures used in the retrospective analysis (32 models applied to 6 weeks over 15 years) precluded convergence testing for all combinations of aggregate model, week, and year.

Results

Uniqueness of solutions and posterior convergence

The forecasting procedure failed to converge in the Quasi-Newton minimization step for one or more years in the retrospective analysis for 16 aggregate models in week 28, 4 aggregate models in each of weeks 29 and 30, and 9 aggregate models in week 31 (Appendix 3). These failures generally occur when solutions (i.e., parameter estimates of the models) are not unique. For week 28, the common element in all 16 of the failed forecasting procedures was inclusion of boundary troll fishery (BT) CPUE data. In this case, the estimation procedure failed in 1994 when the CWT model alone forecast a high marine survival rate compared to the BT index, which forecast exceptionally low marine survival (Table 3). For weeks 29 and 30, aggregate model failures were associated with inclusion of the Tree Point (TP), BT, and pink salmon (PK) catch indices. Whenever all three of these datasets were used together, the estimation procedure failed in 1995; likely because the BT and TP indices contradicted both the high marine survival rate indicated by the CWT model alone and the high index value observed for the PK fishery in this year (Tables 3, 4, and 5). We could not find a consistent explanation for the 9 failures in week 31. All models using four or more aggregate indices and three of the models using three aggregate indices failed to converge to unique solutions in the initial Quasi-Newton step, indicating that there may have been multiple sources of contradiction among the alternative indices in this week. Thus, we did not consider these models any further.

For models that provided unique solutions in the initial Quasi-Newton step, visual inspections of simulated posterior distributions suggested that none of the MCMC chains failed to converge on the target distribution. All posterior distributions were unimodal and the average parameter values within Markov chains remained stable after the burn-in period was removed (Appendix 4). The potential scale reduction factors, $\Re$, for each parameter in each forecasting method also indicated that further improvements in posterior distribution properties were not likely even if the simulations continued indefinitely ($\Re < 1.2$).

Forecast model performance

Marine survival rate forecasting performance as measured by differences between forecasts and post-season estimates for Toboggan Creek coho varied according to model combination and statistical week, but in general, the CWT model tended to dominate performance (e.g., Table 8). During the first four forecasting weeks (27-30), CWT model forecast accuracy (MAE and MRE) and precision (RMSE) were all improved by combining the CWT model with the Area 2 sport fishery CPUE (S2) (Table 9). Improvements were largest for MRE, which ranged from 50 – 65%, and were smallest for MAE, which ranged from 15 – 43% (Figure 1). Improvements in all measures by adding S2 were larger for the middle weeks of the forecasting period (28 – 30) compared to other weeks. During the latter two weeks of the forecasting period, however, the CWT model alone provided the highest performance in almost all cases (Tables 8-9). The exception occurred when the CWT model was combined with pink salmon catch and sport CPUE from Area 1 resulting in an 16 % improvement in MRE for week 31 (Figure 1). MAE and RMSE were unchanged by including these indices. By the final forecasting week, (i.e., week 32), the CWT model alone performed best by all performance measures showing a mean absolute error of MAE = 0.014, a mean relative error of 68.41%, and a root mean square error of RMSE = 0.018 (Table 8). Performance summaries for all models and weeks are given in Appendix 3.

Management cost performance

When our decision analysis framework was applied to in-season forecasts obtained from the CWT model, the correct decision was apparent from the first week onwards for 7 of the 15 years in the retrospective analysis (e.g., 2001 in Figure 2; Appendix 5) and for two other years, the correct decision was apparent by the third in-season forecast (e.g., 1992 in Figure 2). Thus, the CWT model suggested the correct conclusion in 60% of the cases (9 out of 15 years) by week 32.

Critically low marine survival rates occurred four times for Toboggan Creek coho between 1991 and 2005. They occurred in 1992, 1995, 1997, and 1998. In two of these years (1992 and 1998), the correct management conclusion, that marine survival was below the critical value, was apparent by the third in-season forecast when the calculated cost became consistently lower for this conclusion (Figure 2; recall that our decision analysis assumes that managers seek to minimize the cost associated with a decision). In the other two years (1995 and 1997) when marine survival was below critical levels, the management cost functions failed to suggest the correct conclusion (i.e., Type II errors; Figure 2). For example, in all six weeks of 1995 the decision analysis indicated that management cost was lower for concluding that marine survival was above critical levels when, in fact, the opposite conclusion was warranted (i.e., marine survival was lower than critical). In 1997, the same sort of failures only occurred from the third week onwards. Such errors would have suggested opening the Canadian coho fishery despite marine survival rates that were well below the suggested critical level.

An example Type I error would have occurred in 2004, when post-season estimates of marine survival were above critical levels. In this case, the decision analysis consistently indicated lower costs associated with concluding that marine survival was lower than the critical rate. The fishery would have not opened despite a post-season marine survival rate that was above the suggested critical level. For the remaining 6 years in the retrospective analysis, the cost functions were conflicting from week-to-week (e.g., 2002 in Figure 2).

When average management cost was used to measure performance, the ranking of the CWT model was generally lower than most of the aggregate models. In fact, for some cases, the addition of aggregate data (e.g., CWT + TP in statistical week 32) decreased forecasting performance compared to the CWT model alone based on measures of model fit (MAE, MRE, and RMSE), but increased management performance based on average management cost (Table 9).

Improvements in management cost when aggregate catch models are added to the CWT model arise mainly in recent years when most aggregate models provide much larger marine survival rate estimates than indicated by post-season estimates. Such over-estimates cause fewer Type I errors and lower management costs (Table 9). In these cases, the data overwhelmingly support the apparently correct conclusion that marine survival is greater than the critical rate. On the other hand, the CWT model alone, which outperformed these models in terms of forecast accuracy, forecasts marine survival rates that are only slightly less than the post-season estimates. More accurate forecasts by the CWT model increase the chances that a Type I error will be made because they admit that much lower marine survival rates are possible. Interestingly, combining aggregate catch data with the CWT model never resulted in fewer than two Type II errors, which is identical to the number of Type II errors made by the CWT model alone (Table 9).

Discussion

We examined the performance of in-season, marine survival forecasting models that utilize stock-specific coded-wire-tag returns in combination with aggregate catch indices. Specifically, we asked whether forecasting models based on stock-specific CWT data alone could be improved by incorporating one or more indicators of aggregate-stock abundance. We developed a Bayesian forecasting procedure that combined CWT returns with five aggregate catch indices in 32 different ways, and we evaluated performance of this method for the Toboggan Creek coho indicator stock. Retrospective analyses indicated that stock-specific CWT catches in Alaskan boundary troll fisheries provide the most accurate and precise forecasts of Toboggan Creek coho marine survival rates. Small improvements gained by including aggregate catch data in the forecasting procedure diminished as in-season CWT data accumulated. Superior overall performance of the CWT model alone may be attributable to the fact that (i) the catch of CWT coho is stock-specific, (ii) the CWT model combines information across weeks in a given year, (iii) fluctuations in Toboggan Creek smolt output are accounted for, and (iv) fluctuations in troll fishing effort are accounted for. Ultimately, the CWT model uses an informative combination of stock-specific data to forecast a stock-specific metric.

We showed that in the first four weeks of in-season forecasting, marine survival rate forecast accuracy and precision was improved the most by combining CWT returns with aggregate coho CPUE from the Area 2 sport fishery near Haida Gwaii, BC. In the last two weeks of forecasting, however, the CWT model alone tended to outperform all other combinations of CWT and aggregate catch models. The shift in "best" forecasting model from CWT + S2 in the early weeks (27 to 30) to CWT alone during the late weeks (31 and 32) appears to be explained, in part, by improvement in the CWT data as the season progresses. For example, CWT catches in week 27 are highly variable with an among-year coefficient of variation (CV) of 155%. This level of variation is more than double the interannual variation in marine survival rates (68%). Therefore, although sport CPUE may be more indicative of total coho abundance, it probably still contains more information about Toboggan Creek marine survival than CWT data in the first couple of forecasting weeks. Variation in CWT catches decreases relatively quickly during the season reaching CVs of 70 – 80% by weeks 31 and 32. Thus, as CWT catch accumulated, it also became less variable and this appears to improve the estimation accuracy and precision of the CWT model alone for these later weeks. This improved performance was observed in several years of the retrospective analysis where forecasts of marine survival converged toward the post-season estimates with each successive week.

The gains in accuracy and precision achieved by incorporating Area 2 sport fishery data into the CWT forecasting procedure should be viewed with caution because the shorter time series of sport fishery CPUE limits direct performance comparisons between models with and without sport fishery data. Performance metrics for models that do not utilize sport fishery CPUE are calculated based on a sample of 15 years, while performance of models utilizing sport fishery CPUE are based on only four years. Because inferences about forecasting performance are limited to the observed range of variations in true marine survival, return abundances, CWT catches, and catchability, we cannot conclude at this time that the addition of Area 2 sport fishery CPUE clearly improved forecasting performance. Nonetheless, the potential improvement in forecasting performance should warrant continued collection of Area 2 sport fishery CPUE until a longer time series for evaluation can be established.

Although the CWT model performed better on its own than in combination with other aggregate catch models, the frequency of Type I and Type II forecasting errors were higher than previously observed for the CWT model alone when applied to Toboggan Creek (Cox et al. 2003). There are at least three possible reasons for these differences. First, we used in-season boundary troll fishing effort estimates, which are presumably less accurate than the post-season effort estimates used by Cox et al. (2003). Second, we used a higher marine survival rate reference point than Cox et al. (2003), which results in two additional years of critically low marine survival rates and thus, a higher chance of committing a Type II error. We used $s^* = 0.02$ as suggested by Holtby et al. (2000), while Cox et al. (2003) used 50% of the average marine survival observed between 1988 and 1999, which was 0.018. Finally, Cox et al. (2003) use the post-season marine survival rate estimates from 1988 to 1999 to parameterize a prior distribution for their forecasting model. In contrast, we parameterized this prior retrospectively by only allowing post-season marine survival rate estimates for years prior to the forecast. Thus, our prior variance was larger in earlier years (i.e., less informative about the mean) and the mean was probably less accurate, at least in the earlier years. The first and third reasons are significant steps toward evaluating the in-season CWT forecasting procedure in "realistic" situations. Judging by the forecast performance metrics, most of these realistic changes did not degrade forecast performance substantially.

The tendency toward lower management costs for aggregate catch models masks potential risks in choosing forecasting models based on only one type of performance measure. For example, the tendency of some sport-fishery forecasting models to largely overestimate marine survival in recent years resulted in high absolute and relative forecasting errors, but management costs of zero because (i) no critical marine survival rates occurred during the years in which sport CPUE data were available and (ii) forecast errors were so large that Type I errors were extremely unlikely (i.e., probability is near zero that marine survival was below critical level when forecast shows large positive bias). Conversely, the CWT model, which had much lower absolute and relative forecasting errors, had management costs that were among the highest due to (i) the higher number of years in which Type II errors were possible and (ii) small forecast errors that have higher probabilities of committing Type I errors (i.e., more realistic marine survival rate estimates include non-zero probability that marine survival is less than the critical rate).

Other studies also show that the ranking of alternative forecasting models often depends on the metric used to measure performance (Su and Adkison 2002, Haeseker et al. 2005). Of the four performance measures we evaluated, MAE and MRE are likely the most relevant to fisheries managers and industry because they represent the expected forecast bias in any given year. RMSE is also an important metric because it represents the level of confidence that should be placed on annual forecasts from each model. While the relative cost function combined with a decision analysis (Table 7) serves as a potential tool for providing annual harvest advice, it's usefulness as a performance measure was limited by differences in sample size for models with and without sport fishery data and by our arbitrary choices for the costs associated with Type I and Type II errors. In general, we prefer the model rankings based on forecast performance rather than management performance since the potential for mis-interpretation of low management costs is smaller; however, other choices are possible if they provide a consistent means of achieving overall conservation and harvest objectives.

Studies of sockeye run size forecasting suggest that using a Bayesian framework to combine several independent indicators can provide composite forecasts that are more accurate than the least accurate independent forecast, and sometimes more accurate than the most accurate independent forecast (Fried and Hilborn 1988, Cox-Rogers 1997). While we did find that the addition of Area 2 sport fishery CPUE data produced small improvements in forecast accuracy and precision in the early weeks of in-season forecasting, the incorporation of multiple indictors (i.e., all five aggregate indices) did not improve forecasting performance to a large extent. When MAE, MRE, and RMSE were used to measure performance, the CWT model alone always ranked among the top three models.

Whereas sockeye forecasts use mixed-stock data to forecast sockeye abundance for larger stock complexes (Fried and Hilborn 1988; Cox-Rogers 1997), the relatively poor performance of aggregate catch models in our study likely arises because we used aggregated catch data (i.e., over multiple stocks) to forecast marine survival for a single indicator stock. The presence of coho from stocks other than Toboggan Creek in aggregate catches could therefore mask the signal for Toboggan Creek marine survival. For example, although it is well known that coho stocks from Alaska, the central BC coast, and the Queen Charlotte Islands all appear in aggregate coho catches, the forecasting models assume that the proportions of these stocks in aggregate catches remains constant among years. Some evidence against this assumption appears in the forecasts over time. For example, while Tree Point CPUE data combined with the CWT model did a good job of tracking Toboggan Creek marine survival in the early 1990s, marine survival tended to be overestimated in recent years. Such a pattern may result from changes in abundance of Toboggan Creek coho relative to Alaskan stocks. The tendency of the aggregate catch model combining CPUE data from the boundary troll fishery with the CWT model to overestimate marine survival in the last three weeks of in-season forecasting (statistical weeks 30 to 32) is not surprising given that the catch ratio of northern BC coho salmon to southeast Alaska coho salmon starts to decline later in the season (Leon Shaul, ADFG, Douglas, Alaska, pers. comm.). In weeks 27 and 29 however, this model does a relatively good job of tracking annual marine survival for Toboggan Creek coho. In week 29, the combined CWT + boundary troll model actually outperformed the CWT model alone for three of the four performance measures. The aggregate catch model combining Alaskan Pink salmon catch data with the CWT model also did a relatively good job of tracking annual marine survival for most years; however, there were large forecast biases for the years 1999 to 2001. The use of total annual pink salmon catch, as opposed to CPUE, could potentially compromise the predictive strength of this relationship in years when management actions or fishery behaviour affect pink salmon catch levels.

The discrepancies between aggregate and stock-specific coho marine survival or abundance forecasts have rather large implications for long-term management of BC north coast coho fisheries. First, because there is only one coho indicator stock remaining in Statistical Areas 1-5, there is a high risk associated with fisheries decisions for large stock aggregates that are made on the basis of stock-specific forecasts. These risks include over- or under-fishing in any given year. Stock-specific forecasting will almost certainly increase the variability in total annual coho harvest because single stocks tend to fluctuate more so than larger stock aggregates. Second, marine survival alone is probably not the ideal quantity upon which to base harvesting decisions, especially within the current management approach. BC north coast coho fisheries are managed using crude input controls in the form of time-area openings, which places too much emphasis on uncertain forecasts. In other words, the fishery is managed on an “all or nothing” basis; in the present example, a fishery is open or not based on a marine survival rate forecast for a particular. Although we have done our best to incorporate as much information as possible in characterizing the uncertainties and risks associated with these types of decisions, our approach would probably work better within a management system that gradually adjusts exploitation rates in response to both abundance and marine survival. Such a system would likely result in outcomes that are less variable from year-to-year in terms of both coho abundance and harvest.

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Tables and Figures

Table 1. Number of coded-wire-tagged coho salmon released from Toboggan Creek for the return year t (R_t), post-season estimates of marine survival (s_t), and CWT coho catch by the Alaskan boundary troll fishery in week w of year t, ($C_{t,w}$)

Year	R_t	s_t	$C_{t,1}$	$C_{t,2}$	$C_{t,3}$	$C_{t,4}$	$C_{t,5}$	$C_{t,6}$
1988	31476	0.021	0	0	5	6	3	0
1989	30354	0.027	42	8	13	31	24	3
1990	31300	0.041	37	66	20	16	27	11
1991	30954	0.060	12	64	116	56	63	17
1992	31290	0.017	0	11	17	35	24	24
1993	30926	0.029	0	41	29	14	32	22
1994	32600	0.06	5	62	88	73	55	58
1995	33533	0.018	2	6	22	7	8	19
1996	33609	0.025	8	49	20	40	31	18
1997	32368	0.005	0	0	10	10	4	9
1998	33255	0.018	5	10	10	12	7	15
1999	33935	0.104	4	65	76	84	55	71
2000	40351	0.062	0	52	100	82	80	42
2001	35394	0.099	103	60	96	51	56	58
2002	33984	0.035	3	5	19	8	16	13
2003	34333	0.049	9	26	44	27	34	52
2004	34234	0.026	5	22	3	35	22	11
2005	34050	0.033	4	32	39	11	37	7

Table 2. Weekly effort (in thousands of power-troll boat-days) for the Alaskan boundary troll fishery estimated in-season using aerial overflights.

Year	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	$E_{t,6}$
1988	1.28	4.61	4.08	3.59	1.24	1.46
1989	5.40	4.93	5.15	4.61	4.07	3.54
1990	5.42	5.41	4.61	4.70	5.63	0.00
1991	4.92	2.80	3.38	3.51	3.09	4.27
1992	3.24	3.35	4.09	3.83	3.72	3.94
1993	2.50	5.83	4.10	4.27	4.58	2.67
1994	1.37	4.78	3.42	3.85	3.59	4.54
1995	4.74	1.88	2.09	2.39	3.94	4.66
1996	3.29	3.59	2.30	3.21	2.99	2.34
1997	3.57	4.96	2.97	2.96	2.76	1.97
1998	2.45	3.74	2.67	2.84	2.46	2.66
1999	1.70	3.96	2.57	2.76	2.75	0.00
2000	0.55	3.84	2.57	2.79	2.53	2.60
2001	2.80	2.46	2.51	2.58	2.23	2.09
2002	2.12	2.64	2.18	0.97	1.20	0.83
2003	1.87	1.61	1.29	1.14	1.34	0.78
2004	1.46	2.74	2.74	1.82	1.95	1.95
2005	0.87	3.09	2.48	2.48	2.48	2.48

Table 3. Weekly coho CPUE data (catch / day) for the Alaskan Boundary troll fishery.

	Statistical Week						
Year	26	27	28	29	30	31	32
1988	10.27	27.89	15.83	32.24	29.66	30.96	18.58
1989	43.40	26.87	60.14	57.86	55.55	71.18	46.49
1990	54.91	57.64	37.83	40.79	44.16	22.31	35.42
1991	15.83	68.48	102.64	66.94	69.93	69.48	51.24
1992	11.36	23.35	30.02	31.84	38.48	50.11	33.96
1993	24.84	29.03	76.70	66.62	71.94	73.00	55.34
1994	29.72	16.89	109.59	83.40	102.33	140.76	97.25
1995	48.72	12.42	27.11	21.26	26.20	43.60	25.21
1996	18.83	85.01	74.86	80.58	72.92	92.81	66.27
1997	3.33	6.03	8.15	30.00	84.65	81.29	54.25
1998	13.51	33.78	23.73	54.09	100.73	96.41	52.45
1999	38.83	54.79	114.98	114.59	109.39	111.72	104.90
2000	29.26	33.83	84.31	59.53	46.05	104.58	57.65
2001	23.24	58.87	113.80	127.73	125.68	130.02	113.25
2002	11.67	13.80	51.55	66.65	90.65	86.61	49.92
2003	30.13	37.31	84.38	140.34	83.63	105.41	46.56
2004	22.97	42.52	49.55	105.10	117.80	101.07	103.38
2005	53.91	56.35	111.96	195.43	185.44	117.16	168.48

Table 4. Weekly coho CPUE (cumulative catch / hour) data for Tree Point gillnet fishery.

	Statistical Week						
Year	26	27	28	29	30	31	32
1988	2.43	4.00	6.66	9.34	10.27	11.46	2.43
1989	7.62	10.94	13.36	15.67	20.04	22.93	7.62
1990	7.87	11.62	17.32	20.65	27.49	38.26	7.87
1991	2.82	8.15	18.56	22.32	30.00	37.25	2.82
1992	4.78	6.59	7.82	10.17	13.51	18.93	4.78
1993	5.55	7.23	8.35	10.30	14.94	18.05	5.55
1994	3.64	6.05	12.80	17.58	20.66	27.29	3.64
1995	4.57	5.60	7.03	8.87	10.79	14.75	4.57
1996	6.02	9.34	12.20	18.80	23.08	32.51	6.02
1997	0.88	1.65	3.05	4.10	5.69	7.87	0.88
1998	3.16	5.84	12.12	18.58	24.50	34.79	3.16
1999	10.45	23.57	33.17	44.85	51.00	60.23	10.45
2000	2.74	5.91	9.41	13.19	17.14	27.69	2.74
2001	9.04	13.73	18.74	24.71	32.77	53.87	9.04
2002	7.09	21.94	31.41	43.08	54.45	73.83	7.09
2003	12.72	20.56	31.07	50.77	58.68	69.55	12.72
2004	3.23	13.45	22.69	26.61	46.00	59.36	3.23
2005	17.65	26.35	38.83	69.86	80.93	88.53	17.65

Table 5. Total pink salmon catch in Alaskan commercial fisheries (in millions of fish)

Year	Total Catch
1988	11.044
1989	59.219
1990	31.432
1991	60.776
1992	32.824
1993	56.937
1994	53.763
1995	47.530
1996	63.977
1997	27.224
1998	41.065
1999	74.703
2000	20.006
2001	65.807
2002	44.405
2003	52.027
2004	44.337
2005	58.016

Table 6. Coho CPUE data (average number caught / boat day) for the Haida Gwaii sport fishery.

	Area 1		Area 2	
Year	June	July	June	July
1996	0.186	2.022	0.022	0.606
1997	0.132	0.415	0.091	0.763
1998	-	-	-	-
1999	-	-	-	-
2000	0.281	1.777	0.240	2.535
2001	0.724	7.448	2.453	3.397
2002	-	-	-	-
2003	1.395	8.199	1.663	2.576
2004	1.236	6.957	0.329	1.834
2005	0.875	4.401	2.158	3.599

Table 7. Decision matrix containing relative costs for all possible states of nature (columns) and conclusions (rows) drawn from the forecasting models. A cost of 1 is assigned to lost fishing opportunity (upper right cell), while a cost of 2 is assigned to over-fishing (lower left cell). These costs are arbitrarily chosen for demonstration purposes, although they have been show to provide reasonable long-term performance in limiting both types of errors (Cox et al. 2003).

	State of Nature	
Conclusion	$s_t \leq s^*$	$s_t > s^*$
$s_t \leq s^*$	0	1
$s_t > s^*$	2	0

Table 8. Forecasting and management performance in retrospective analyses (Week 32) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

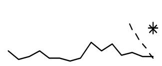
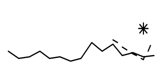
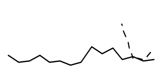
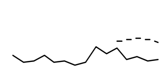
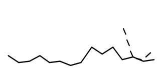
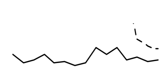
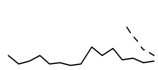
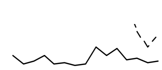
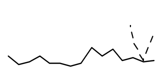
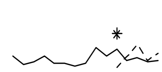
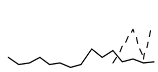
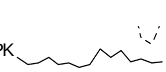
Model	Marine Survival	MAE	MRE	RMSE	Cost	Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.014	68	0.018	0.47	CWT, TP, BT, S1		0.088	200	0.108	0
CWT, TP		0.049	140	0.072	0.27	CWT, TP, BT, S2		0.043	101	0.054	0
CWT, BT		0.401	1066	0.568	0.47	CWT, TP, BT, PK		0.055	204	0.077	0.47
CWT, S1		0.127	219	0.164	0.25	CWT, TP, S1, S2		0.093	241	0.101	0
CWT, S2		0.03	84	0.045	0.25	CWT, TP, S1, PK		0.194	343	0.245	0
CWT, PK		0.039	98	0.055	0.47	CWT, TP, S2, PK		0.201	348	0.257	0
CWT, TP, BT		0.052	176	0.073	0.4	CWT, BT, S1, S2		0.095	142	0.139	0
CWT, TP, S1		0.093	241	0.1	0	CWT, BT, S1, PK		0.045	82	0.058	0.25
CWT, TP, S2		0.083	223	0.093	0	CWT, BT, S2, PK		0.056	104	0.066	0.25
CWT, TP, PK		0.051	151	0.075	0.4	CWT, S1, S2, PK		0.114	265	0.135	0.25
CWT, BT, S1		0.086	122	0.14	0	CWT, TP, BT, S1, S2		0.087	242	0.092	0
CWT, BT, S2		0.09	126	0.149	0	CWT, TP, BT, S1, PK		0.215	389	0.259	0
CWT, BT, PK		0.083	229	0.153	0.53	CWT, TP, BT, S2, PK		0.179	296	0.248	0
CWT, S1, S2		0.109	202	0.131	0	CWT, TP, S1, S2, PK		0.207	376	0.254	0
CWT, S1, PK		0.29	406	0.455	0	CWT, BT, S1, S2, PK		0.056	104	0.066	0.25
CWT, S2, PK		0.124	303	0.147	0	CWT, TP, BT, S1, S2, PK		0.229	456	0.269	0

Table 9. First ranked model ("best") for each performance measure (MAE = mean relative error, MRE = mean relative error, and RMSE = root mean square error) in each week of in-season management. CWT = coded wire tag model, S1 and S2 = Area 1 and Area 2 sport fishery, Haida Gwaii, and PK = Alaskan pink salmon fishery.

	Performance measure		
Week	**MAE**	**MRE**	**RMSE**
27	CWT + S2	CWT + S2	CWT + S2
28	CWT + S2	CWT + S2	CWT + S2
29	CWT + S2	CWT + S2	CWT + S2
30	CWT + S2	CWT + S2	CWT + S2
31	CWT	CWT + PK + S1	CWT
32	CWT	CWT	CWT

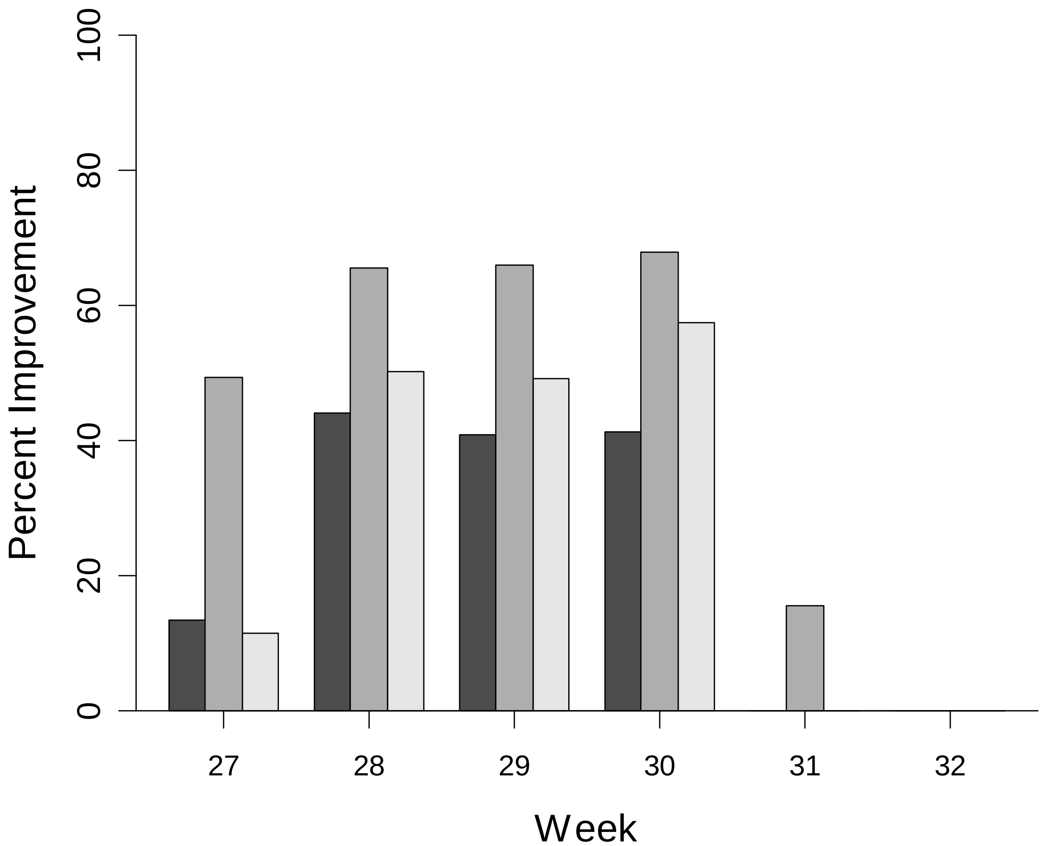


Figure 1. Percent improvement in mean absolute error (dark grey bars), mean relative error (medium grey bars), and root mean square error (light grey bars) obtained for each week by using the "best" model from Table 9 compared to the CWT model alone. Missing bars indicate that the CWT model was the "best" model for a given performance measure in a given week.

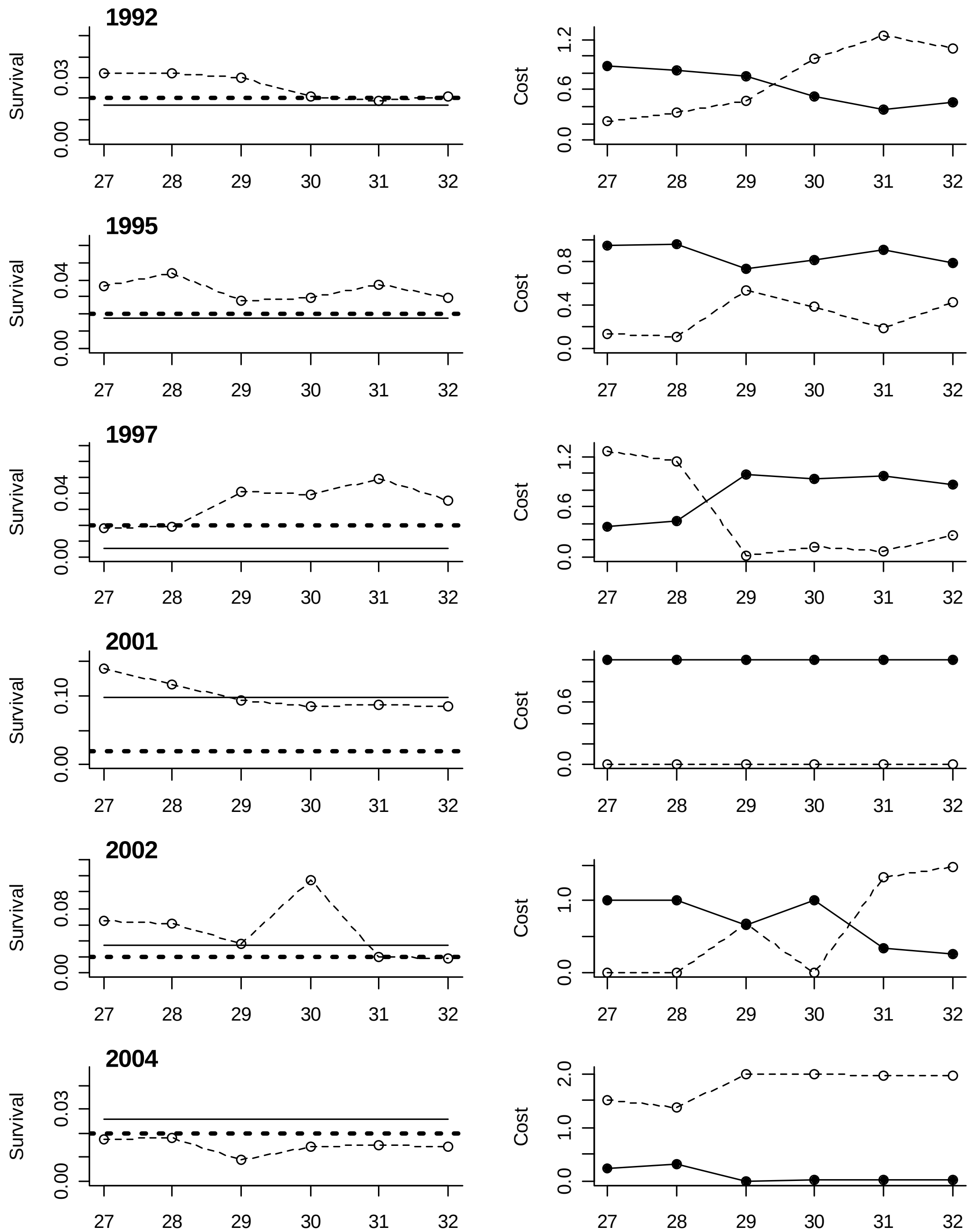


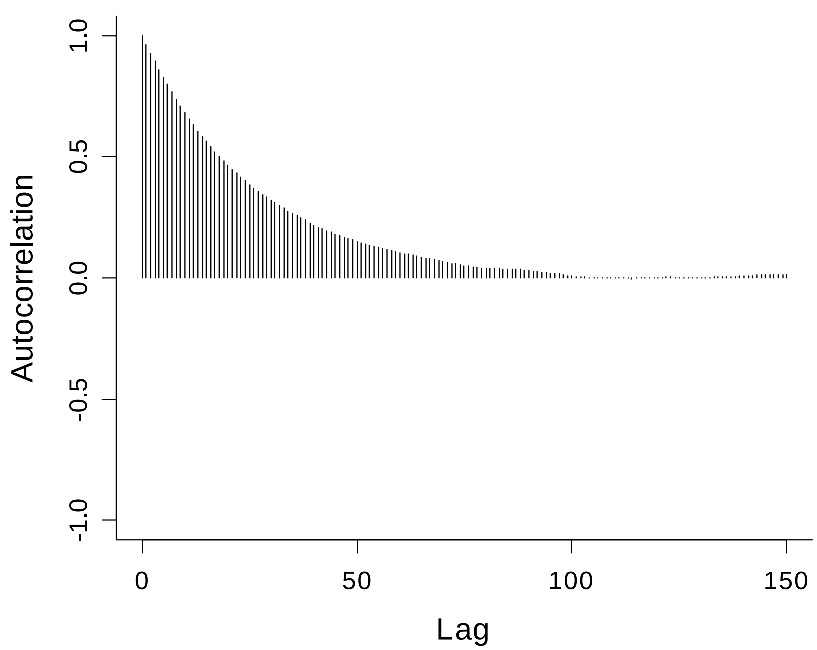
Figure 2. Left column: Results of the retrospective analysis showing weekly estimates of annual marine survival (open circles and thin dashed lines), observed post-season estimates of annual marine survival (solid lines), and the critical survival rate, s^* (thick dashed line) for a subset of years. Right column: Expected costs of concluding that marine survival is greater than s^* (open circles and dashed lines) and that marine survival is less than s^* (closed circles and solid lines) based on data up to each week corresponding to the years in the left column.

Appendices

Appendix 1

The level of autocorrelation within individual Markov chains was monitored to determine an appropriate thinning interval. High levels of autocorrelation can result in slow convergence, and thus, sequences are often thinned to improve simulation efficiency by keeping only every k^{th} simulation draw and discarding the rest (Gelman et al. 2004). Initial runs of the MCMC routine produced high autocorrelations for all estimated parameters (lag 1 autocorrelation coefficients ranging from 0.8 to 0.95; where lag values are relative to thinning intervals). Evaluation of the autocorrelation function at increasing levels of lag showed that autocorrelation decreased slowly with increasing lag values for all parameters (e.g., Figure A1). A lag value of 100 was necessary to achieve autocorrelation near zero.

Figure A1-1. Example of diagnostic plot used to select a thinning interval for Markov chains.



Appendix 2

Table A2-1. Combinations of week, year, and aggregate models that were randomly selected for testing whether MCMC posterior distributions converged on target distributions. CWT = coded wire tag model, S1 and S2 = Area 1 and Area 2 sport fishery, Haida Gwaii, and PK = Alaskan pink salmon fishery.

Week	Year	Aggregate Model
27	6	CW + BT + PK
27	8	CW + TP + BT + PK
27	13	CW + TP + S1 + PK
27	13	CW + BT + S1 + PK
27	14	CW + TP + S1 + PK
27	17	CW + TP + S1 + PK
28	12	CW + TP + S2
28	15	CW + TP + S1 + S2
29	8	CW + S2
29	8	CW + BT + S1 + S2 + PK
29	12	CW + TP + S1
29	14	CW + BT + S1 + PK
30	9	CW + BT
30	12	CW + TP + BT + S2
30	13	CW + TP + PK
31	10	CW + S1 + S2
31	16	CW + S1 + PK
32	6	CW + TP + BT + S1 + S2
32	9	CW + TP
32	16	CW + S2 + PK

Appendix 3

Table A3-1. Forecasting and management performance in retrospective analyses (Week 27) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.023	69	0.027	0.53
CWT, TP		0.06	256	0.104	0.67
CWT, BT		0.034	108	0.051	0.27
CWT, S1		0.239	331	0.352	0.25
CWT, S2		0.02	35	0.024	0.25
CWT, PK		0.039	98	0.055	0.47
CWT, TP, BT		0.033	106	0.05	0.27
CWT, TP, S1		0.129	286	0.149	0.25
CWT, TP, S2		0.107	261	0.137	0.25
CWT, TP, PK		0.038	100	0.055	0.47
CWT, BT, S1		0.06	148	0.07	0
CWT, BT, S2		0.054	141	0.066	0
CWT, BT, PK		0.032	100	0.043	0.47
CWT, S1, S2		0.099	197	0.168	0.25
CWT, S1, PK		0.149	356	0.176	0.25
CWT, S2, PK		0.131	340	0.171	0
CWT, TP, BT, S1		0.053	143	0.065	0
CWT, TP, BT, S2		0.092	220	0.115	0
CWT, TP, BT, PK		0.031	98	0.04	0.33
CWT, TP, S1, S2		0.105	268	0.139	0.25
CWT, TP, S1, PK		0.332	515	0.469	0
CWT, TP, S2, PK		0.31	495	0.424	0
CWT, BT, S1, S2		0.057	142	0.069	0
CWT, BT, S1, PK		0.309	827	0.492	0
CWT, BT, S2, PK		0.122	247	0.136	0
CWT, S1, S2, PK		0.138	348	0.175	0
CWT, TP, BT, S1, S2		0.101	240	0.125	0
CWT, TP, BT, S1, PK		0.094	183	0.115	0
CWT, TP, BT, S2, PK		0.128	259	0.146	0
CWT, TP, S1, S2, PK		0.326	500	0.462	0
CWT, BT, S1, S2, PK		0.127	259	0.141	0
CWT, TP, BT, S1, S2, PK		0.126	252	0.143	0

Table A3-2. Forecasting and management performance in retrospective analyses (Week 28) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

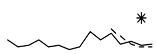
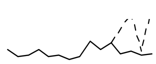
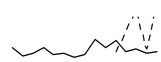
Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.021	74	0.025	0.53
CWT, TP		0.053	139	0.077	0.33
CWT, BT	No Solution				
CWT, S1		0.184	218	0.322	0.25
CWT, S2		0.012	26	0.013	0.25
CWT, PK		0.039	99	0.055	0.47
CWT, TP, BT	No Solution				
CWT, TP, S1		0.101	253	0.117	0
CWT, TP, S2		0.093	246	0.115	0
CWT, TP, PK		0.036	106	0.046	0.47
CWT, BT, S1	No Solution				
CWT, BT, S2	No Solution				
CWT, BT, PK	No Solution				
CWT, S1, S2		0.102	207	0.183	0.25
CWT, S1, PK		0.148	355	0.175	0.25
CWT, S2, PK		0.126	334	0.17	0
CWT, TP, BT, S1	No Solution				
CWT, TP, BT, S2	No Solution				
CWT, TP, BT, PK	No Solution				
CWT, TP, S1, S2		0.096	247	0.118	0
CWT, TP, S1, PK		0.312	458	0.462	0
CWT, TP, S2, PK		0.298	448	0.429	0
CWT, BT, S1, S2	No Solution				
CWT, BT, S1, PK	No Solution				
CWT, BT, S2, PK	No Solution				
CWT, S1, S2, PK		0.143	352	0.176	0
CWT, TP, BT, S1, S2	No Solution				
CWT, TP, BT, S1, PK	No Solution				
CWT, TP, BT, S2, PK	No Solution				
CWT, TP, S1, S2, PK		0.305	439	0.453	0
CWT, BT, S1, S2, PK	No Solution				
CWT, TP, BT, S1, S2, PK	No Solution				

Table A3-3. Forecasting and management performance in retrospective analyses (Week 29) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

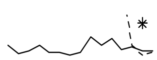
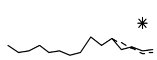
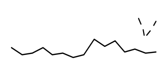
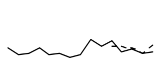
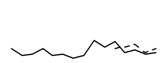
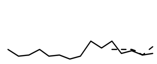
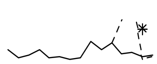
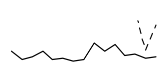
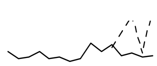
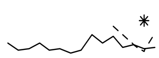
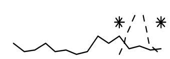
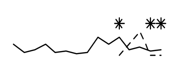
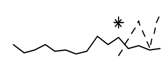
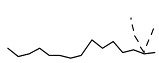
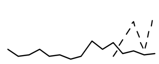
Model	Marine Survival	MAE	MRE	RMSE	Cost	Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.014	77	0.02	0.6	CWT, TP, BT, S1		0.021	42	0.023	0
CWT, TP		0.043	113	0.064	0.2	CWT, TP, BT, S2		0.026	52	0.03	0
CWT, BT		0.015	37	0.02	0.13	CWT, TP, BT, PK	No Solution				
CWT, S1		0.17	191	0.323	0.25	CWT, TP, S1, S2		0.132	338	0.16	0
CWT, S2		0.008	26	0.01	0.25	CWT, TP, S1, PK		0.345	551	0.473	0
CWT, PK		0.039	98	0.055	0.47	CWT, TP, S2, PK		0.333	541	0.45	0
CWT, TP, BT		0.014	36	0.019	0.13	CWT, BT, S1, S2		0.023	47	0.029	0
CWT, TP, S1		0.135	342	0.159	0	CWT, BT, S1, PK		0.014	36	0.019	0
CWT, TP, S2		0.129	336	0.157	0	CWT, BT, S2, PK		0.02	48	0.024	0
CWT, TP, PK		0.042	120	0.059	0.47	CWT, S1, S2, PK		0.141	351	0.175	0
CWT, BT, S1		0.022	46	0.027	0	CWT, TP, BT, S1, S2		0.027	56	0.028	0
CWT, BT, S2		0.022	46	0.028	0	CWT, TP, BT, S1, PK	No Solution				
CWT, BT, PK		0.015	37	0.02	0	CWT, TP, BT, S2, PK	No Solution				
CWT, S1, S2		0.087	187	0.16	0.25	CWT, TP, S1, S2, PK		0.333	512	0.466	0
CWT, S1, PK		0.149	357	0.176	0.25	CWT, BT, S1, S2, PK		0.02	50	0.024	0
CWT, S2, PK		0.13	339	0.17	0	CWT, TP, BT, S1, S2, PK	No Solution				

Table A3-4. Forecasting and management performance in retrospective analyses (Week 30) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.018	85	0.028	0.47
CWT, TP		0.058	153	0.094	0.2
CWT, BT		0.072	182	0.106	0.13
CWT, S1		0.174	191	0.333	0.5
CWT, S2		0.011	27	0.012	0.5
CWT, PK		0.039	98	0.055	0.47
CWT, TP, BT		0.06	160	0.096	0.13
CWT, TP, S1		0.171	433	0.226	0
CWT, TP, S2		0.174	436	0.225	0
CWT, TP, PK		0.058	154	0.09	0.4
CWT, BT, S1		0.163	341	0.181	0
CWT, BT, S2		0.145	323	0.159	0
CWT, BT, PK		0.067	179	0.104	0.13
CWT, S1, S2		0.08	169	0.143	0.5
CWT, S1, PK		0.148	355	0.175	0.25
CWT, S2, PK		0.133	341	0.17	0
CWT, TP, BT, S1		0.142	326	0.157	0
CWT, TP, BT, S2		0.132	313	0.148	0
CWT, TP, BT, PK	No Solution				
CWT, TP, S1, S2		0.176	437	0.227	0
CWT, TP, S1, PK		0.38	639	0.488	0
CWT, TP, S2, PK		0.329	580	0.404	0
CWT, BT, S1, S2		0.145	324	0.159	0
CWT, BT, S1, PK		0.328	510	0.47	0
CWT, BT, S2, PK		0.319	502	0.452	0
CWT, S1, S2, PK		0.142	351	0.176	0
CWT, TP, BT, S1, S2		0.134	317	0.15	0
CWT, TP, BT, S1, PK	No Solution				
CWT, TP, BT, S2, PK	No Solution				
CWT, TP, S1, S2, PK		0.337	585	0.419	0
CWT, BT, S1, S2, PK		0.325	507	0.464	0
CWT, TP, BT, S1, S2, PK	No Solution				

Table A3-5. Forecasting and management performance in retrospective analyses (Week 31) of alternative models that combine Toboggan Creek coho coded-wired tag returns (CWT) with aggregate catch data from the Tree Point test fishery (TP), Alaskan boundary troll fishery (BT), Area 1 and 2 sport fisheries off Haida Gwaii, BC (S1 and S2), and Alaskan pink salmon catch (PK). The time series plots show marine survival forecasts (dashed line) and post-season estimates (solid lines) for 1991 to 2005. Type I (asterisks) and Type II (stars) errors are marked above the years in which they occur. MAE = mean absolute error, MRE = mean relative error, RMSE = root mean square error, and Cost = average management cost based on calculations in Table 7.

Model	Marine Survival	MAE	MRE	RMSE	Cost	Model	Marine Survival	MAE	MRE	RMSE	Cost
CWT		0.016	89	0.021	0.53	CWT, TP, BT, S1	No Solution				
CWT, TP		0.058	159	0.091	0.27	CWT, TP, BT, S2		0.227	372	0.298	0.25
CWT, BT		0.313	942	0.498	0.47	CWT, TP, BT, PK	No Solution				
CWT, S1		0.127	218	0.165	0	CWT, TP, S1, S2		0.169	459	0.201	0
CWT, S2		0.037	85	0.048	0.25	CWT, TP, S1, PK		0.402	731	0.482	0
CWT, PK		0.039	98	0.055	0.47	CWT, TP, S2, PK		0.364	623	0.474	0
CWT, TP, BT		0.06	231	0.088	0.4	CWT, BT, S1, S2		0.1	196	0.134	0.5
CWT, TP, S1		0.203	525	0.239	0	CWT, BT, S1, PK		0.059	114	0.067	0.75
CWT, TP, S2		0.156	415	0.189	0	CWT, BT, S2, PK	No Solution				
CWT, TP, PK		0.061	170	0.093	0.53	CWT, S1, S2, PK		0.115	266	0.136	0.25
CWT, BT, S1		0.04	76	0.053	0.5	CWT, TP, BT, S1, S2	No Solution				
CWT, BT, S2		0.268	871	0.395	0.5	CWT, TP, BT, S1, PK	No Solution				
CWT, BT, PK		0.136	430	0.271	0.33	CWT, TP, BT, S2, PK	No Solution				
CWT, S1, S2		0.106	199	0.126	0	CWT, TP, S1, S2, PK	No Solution				
CWT, S1, PK		0.289	406	0.455	0	CWT, BT, S1, S2, PK	No Solution				
CWT, S2, PK		0.125	303	0.148	0	CWT, TP, BT, S1, S2, PK	No Solution				

Appendix 4

Figure A4-1. Example of a Markov chain sequence used to visually inspect posterior distributions for indications of failure to converge on the target distribution. A trend in the smoothed line would be an indication of convergence failure.

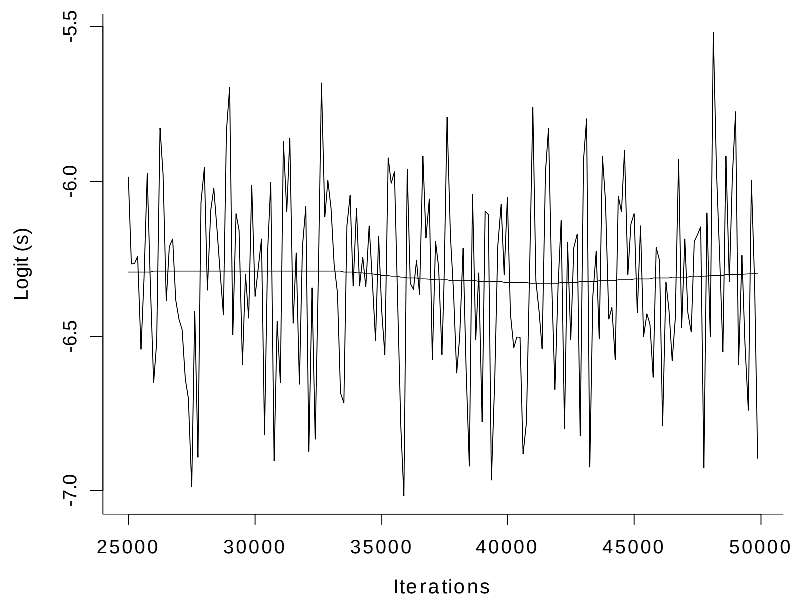
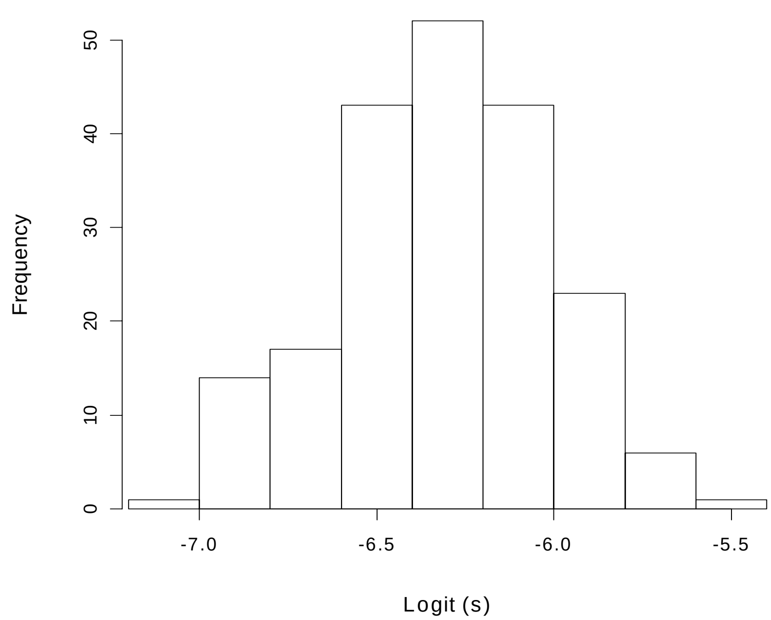


Figure A4-2. Example of a histogram of posterior sample points used to visually inspect posterior distributions for indications of failure to converge on the target distribution. An unsmooth of bimodal distribution would be an indication of convergence failure.



Appendix 5

Figure A5-1. Left column: Results of the retrospective analysis showing weekly estimates of annual marine survival (open circles and thin dashed lines), observed post-season estimates of annual marine survival (solid lines), and the critical survival rate, s^* (thick dashed line) for each year in the analysis. Right column: Expected costs of concluding that marine survival is greater than s^* (open circles and dashed lines) and that marine survival is less than s^* (closed circles and solid lines) based on data up to each week corresponding to the years in the left column.

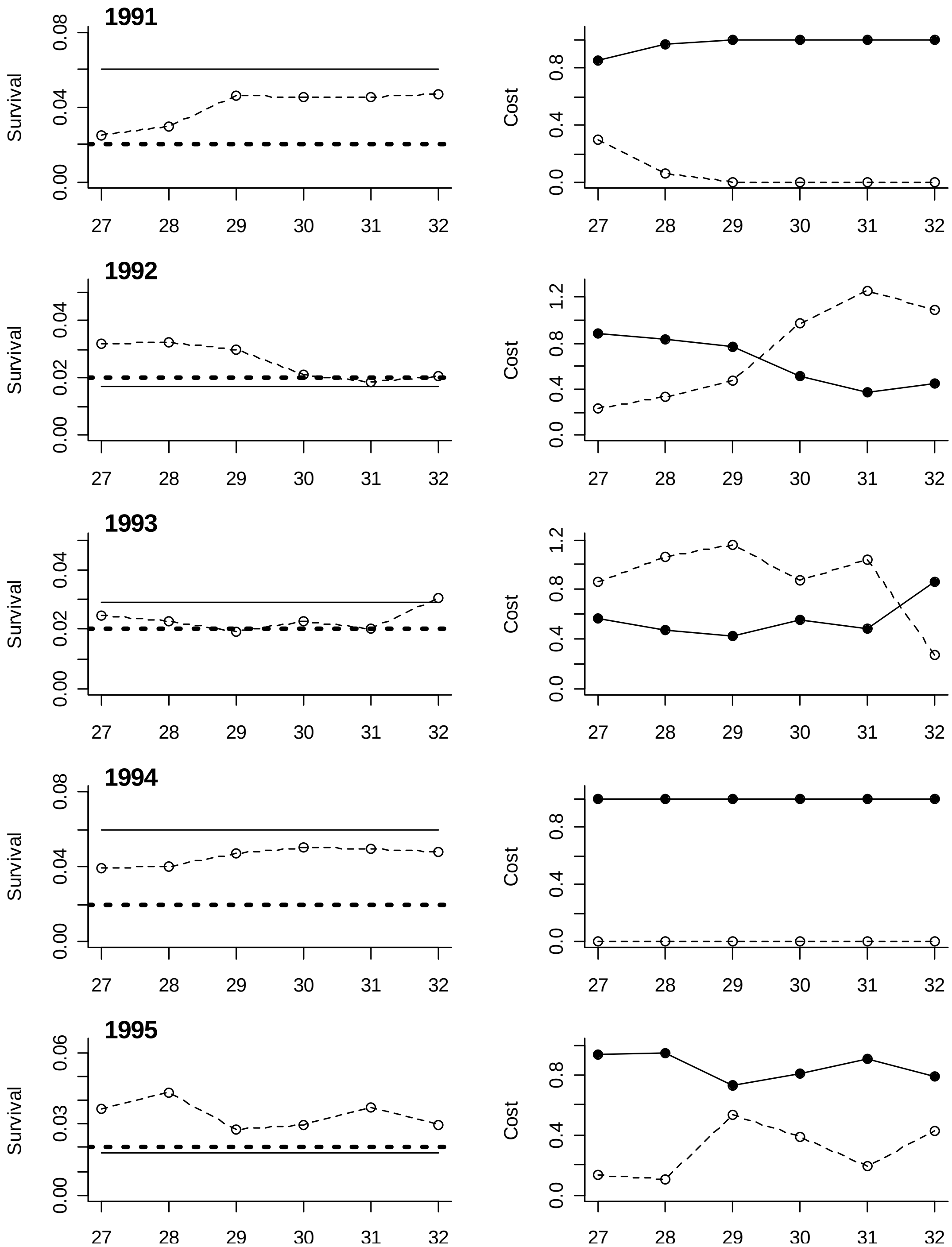


Figure A5-1. cont.

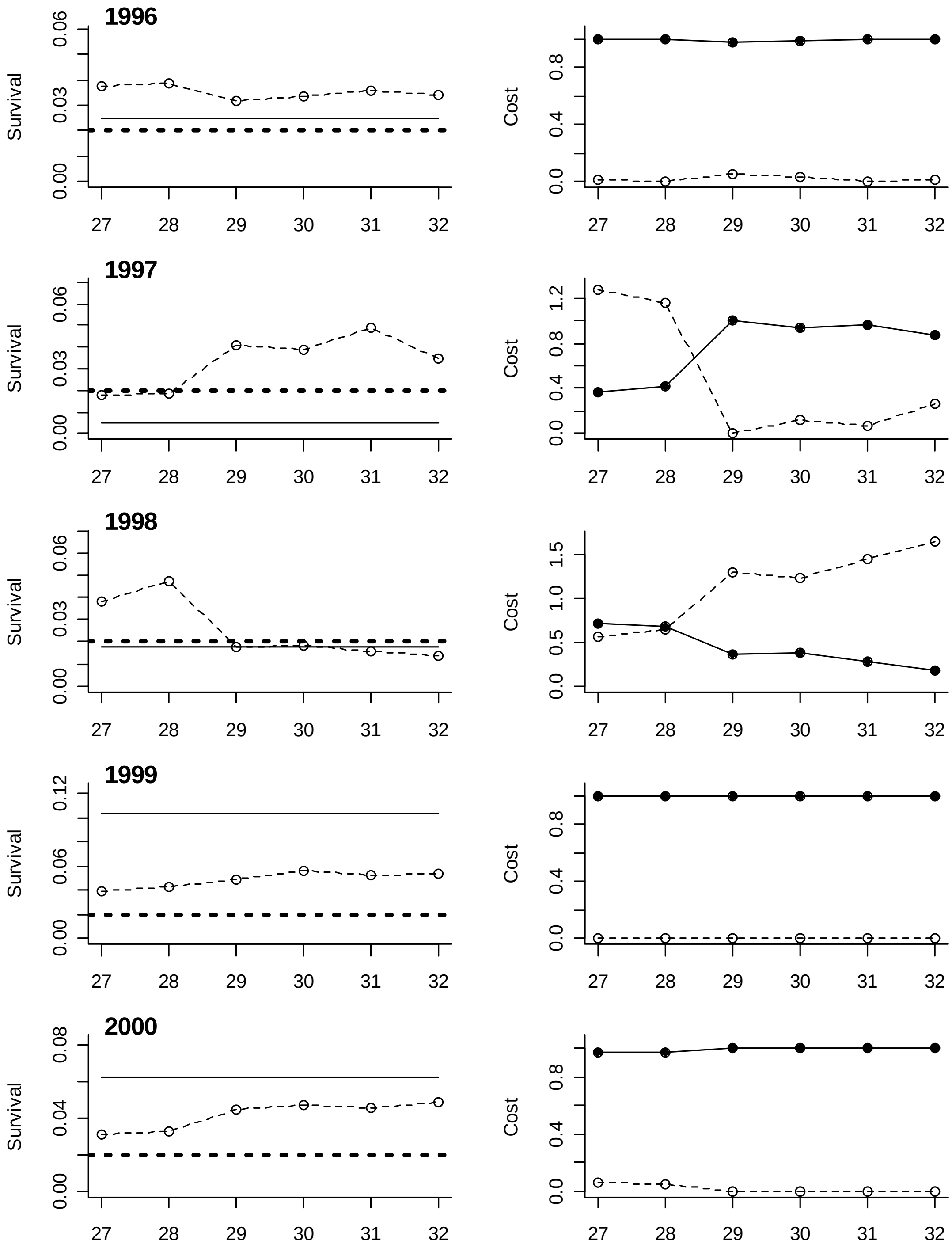


Figure A5-1. cont. 2