Quantifying the Sensitivity of Fraser River Sockeye Salmon (*Oncorhynchus nerka*) Management Adjustment Models to Uncertainties in Run Timing, Run Shape and Run Profile

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by

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ABSTRACT

Hague, M.J. and Patterson, D.A. 2007. Quantifying the sensitivity of Fraser River sockeye salmon (*Oncorhynchus nerka*) management adjustment models to uncertainties in run timing, run shape and run profile. Can. Tech. Rep. Fish. Aquat. Sci. 2776: 55 + vii p.

Differences between lower and upper river sockeye salmon escapement estimates (difference between estimates; DBEs) are currently forecasted from average river temperature and discharge conditions using Management Adjustment (MA) models. MA models were developed on the underlying biological assumption of a link between extreme river environment and increased en route mortality. If the relationship between environmental exposure and fish mortality drives the observed DBEs, we hypothesised the use of environmental averages weighted by the proportion of the daily incoming run would produce more accurate DBE forecasts than the currently applied 31-day symmetric or 19-day asymmetric un-weighted averages. The length, shape, and timing of incoming run distributions at a fixed location in the lower river (Hells Gate, B.C.) displayed high annual variability. Early Stuart runs averaged 34 days in length (± 6 days), Early Summer runs 52 days (± 12 days), Summer runs 63 days (± 12 days), and Late runs 46 days (± 13 days). Early Summer and Late run distributions were often negatively skewed and the occurrence of multiple modes was common. Run distributions were rarely normally distributed, and were best-fit using a mixed normal model. The complexity of the run distributions was not accurately reflected by 31-day or 19-day means; however, the 31-day MA models consistently provided a better fit to historic DBEs than the weighted average MA models. Across a range of environmental scenarios, weighted average MA models were relatively robust to changes in the shape of the incoming run, but were sensitive to changes in run timing. Sensitivity to run timing for weighted 31- and 19-day MA models was highest during the early summer and during years of extreme and highly variable environmental conditions. Uncertainty analyses revealed limited improvements to DBE forecasts if run timing uncertainty was included in the Early Stuart MA models. Our current inability to predict accurate daily river conditions and daily abundance inhibits the use of weighted average models for forecasting DBEs. We recommend continued use of 31-day symmetric environmental averages as a reasonable surrogate for the effect of river temperature and discharge on spawning escapement discrepancies. However, we also recommend the investigation of cumulative exposure models as an alternative method for modeling river conditions experienced by migrating sockeye salmon.

RESUMÉ

Hague, M.J. and Patterson, D.A. 2007. Quantifying the sensitivity of Fraser River sockeye salmon (*Oncorhynchus nerka*) management adjustment models to uncertainties in run timing, run shape and run profile. Can. Tech. Rep. Fish. Aquat. Sci. 2776: 55 + vii p.

Les différences entre les évaluations d'échappée de saumon rouge entre le cours inférieur et le cours supérieur du Fraser (différences entre évaluations; DEE) sont actuellement prédites grâce à des modèles de gestion ajustée (GA), se basant sur la température moyenne du fleuve et les conditions d'écoulement. Les modèles de gestion ajustée ont été développés en se fondant sur l'hypothèse d'un lien entre des conditions extrêmes du fleuve et une forte mortalité de montaison. Si le lien entre les conditions environnementales et la mortalité des saumons explique les DEE observées, nous avons émis l'hypothèse qu'utiliser des moyennes environnementales pondérées par la migration quotidienne fournirait des prévisions des DEE plus précises que celles obtenues pour des moyennes non pondérées, respectivement asymétriques et symétriques, de 19 jours ou 31 jours. On observe une forte variabilité annuelle pour la forme, la durée et la période des courbes de repartitions des migrations. La durée moyenne de la migration des Early Stuart est de 34 jours (± 6 jours), 52 jours pour les Early

Summer (± 12 jours), 63 jours pour les Summer (± 12 jours) et 46 jours pour les Late (± 13 jours). Les répartitions de la migration des Early Summer et des Late étaient souvent asymétriques, plusieurs migrations différentes se chevauchant frequemment. Les répartitions de migration avaient rarement une distribution normale, et étaient plus en accord avec un modèle normal composé. La complexité de la répartition des migrations n'était pas exactement reflétée par les moyennes de 31 ou 19 jours; néanmoins, les modèles de GA sur 31 jours ont toujours donné un résultat plus en accord avec les DEE historiques que les modèles de GA avec moyenne pondérée. Parmi une variété de scénarios environnementaux, les modèles de GA avec moyenne pondérée étaient plutôt robustes aux changements de répartition des migrations, mais étaient sensibles aux changements d'époques de migration. La sensibilité à l'époque de migration pour les modèles de GA, pondérés sur 31 jours ou 19 jours, a été la plus forte au debut de l'été et durant les années de conditions environnementales extrêmes et très variables. Les analyses des incertitudes ont revélé des améliorations limitées pour les prévisions des DEE lorsque l'incertitude de l'époque de migration était incluse dans les modèles de GA pour les Early Stuart. Notre incapacité actuelle à prédire les caractéristiques journalières du fleuve et l'abondance quotidienne empêche l'utilisation de modelès à moyenne pondérée pour les prévisions des DEE. Nous recommandons d'utiliser les moyennes environnementales symétriques sur 31 jours comme remplaçants cohérents pour l'effet de la température et de l'écoulement du fleuve sur les différences d'échappée sur les lieux de frai. Cependant, nous recommandons également l'essai de modèles d'exposition cumulée comme méthode alternative pour modéliser les conditions environnementales réellement rencontrées par les saumons rouges en migration.

INTRODUCTION

One of the key management objectives of the Fraser River, BC sockeye salmon (*Oncorhynchus nerka)* fishery is the achievement of spawning escapement targets (SETs; a target number of returning adult fish that complete the migration to the spawning grounds; Figure 1). However, one of the many challenges associated with achieving escapement objectives is accounting for the uncertain difference between the number of fish estimated during lower-river escapement enumerations measured at a hydroacoustic facility at Mission (operated by the Pacific Salmon Commission; PSC), and the number of spawners estimated on the spawning grounds by Fisheries and Oceans Canada (DFO) stock assessment after accounting for DFO's estimates of in-river catches (Figure 1). This difference between estimates, hereafter referred to as DBEs, may be attributed to several sources including: errors in estimates of escapement at Mission (Xie et al. 2002), errors in spawning ground escapement estimates (Schubert 1997), errors in in-river catch estimates, unaccounted-for river catches, fishery-induced mortality and natural mortality (Macdonald et al. 2000; Patterson et al. 2007a). Because the escapement discrepancy is typically negative (up-river escapement is less than Mission escapement), additional numbers of fish are allowed to pass up-river to adjust for the expected difference between the fish estimated at Mission and those estimated in catches upstream and on the spawning grounds. The additional number of fish allowed to escape up-river is referred to as the "Management Adjustment" (MA). During both the pre-season and in-season, salmon managers utilise the relationship between river environmental conditions and historic DBEs to estimate the required MAs. The MAs are applied to the allowable catch (I. Guthrie, PSC, pers. comm. 2006) to increase the probability of achieving spawning escapement targets. Although management has become reliant on forecasts of summer river conditions, they currently apply this environmental information in the absence of a solid understanding of the relationship between the true river conditions experienced by the run and the associated DBEs.

A correlation between increased in-river fish mortality and extreme river summer environmental conditions (high temperature, high flow) has been well-recognised (e.g. Macdonald et al. 2000a; Macdonald et al. 2000b). Since 2001, Management Adjustment models (MA models) developed by the PSC and DFO (Macdonald et al. unpub; I. Guthrie, PSC, pers. comm. 2006) have fit historic DBEs to average Qualark river temperature and Hope discharge values (Figure 1). For management purposes, returning stocks are divided into four major groups based on their historic return times to the river: Early Stuart, Early Summer, Summer and Late-run (Gable and Cox-Rogers 1993). The current Early Stuart, Early Summer and Summer-run MA models predict DBEs using non-linear simple and multiple regressions (e.g. Eq. 1) as a function of average river temperature and/or discharge conditions centred on the date at which 50% of each run passes Hells Gate (hereafter referred to as the 50% date).

Eq. 1

$$\ln\left(\frac{SE}{PSE}\right) = a + b_1 T + b_2 T^2 + b_3 Q + b_4 Q^2$$

where *SE* is the spawning ground escapement, *PSE* is the potential Mission spawning escapement (Mission escapement estimate – upriver catches), *T* is a measure of average temperature measured at Qualark (°C) (Figure 1), and Q is a measure of average discharge measured at Hope (cms) (Figure 1).

Recent extreme changes in arrival timing observed for Late-run sockeye have dramatically increased the duration of freshwater residence before spawning (Lapointe et al. 2003; Cooke et al. 2004). These earlier Late-run 50% dates have been closely correlated to changes in river temperature and discharge exposure (Patterson et al. 2007b) and to negative escapement discrepancies and high mortality (St. Hilaire et al. 2002; Cooke et al. 2004; Young et al. 2006; Crossin et al. 2007). Therefore, Late-run sockeye MA models are currently a function of the forecasted 50% date (Eq. 2)

Eq. 2

$$\ln\left(\frac{SE}{PSE}\right) = a + b_1 D_{50}$$

where and D_{50} is the Late-run Hells Gate 50% date.

Run-specific management adjustment model parameters are estimated by fitting historic discrepancy data to historic environmental or run timing conditions using Equations 1 and 2 respectively.

Current forecasting limitations and management restraints necessitate the use of separate pre-season and in-season environmental and MA forecasting models. Pre-season environmental models utilise historic relationships between river temperature and discharge and other related environmental variables to produce 31-day symmetric environmental averages centred on the Hells Gate 50% date (Patterson and Hague 2007). The 31-day timeframe was selected to represent the average lower river conditions experienced by an incoming run. In-season, daily temperature and discharge forecasts are produced for a 9-day period using complex hydrological models (Morrison 2005; Morrison and Foreman 2005). Due to declining accuracy of longer range forecasts, it is currently inefficient to produce a longer time series of predictions (Morrison 2005). The daily in-season forecasts are combined with observed temperature and discharge values to predict 19-day asymmetric environmental averages (15-days before and 3-days after the 50% date). The shorter, asymmetric model accommodates both limits to the daily forecasting capacity, and the need to provide in-season updates prior to the peak of the run entering the Fraser River to be able to adjust harvest levels accordingly. As the run enters the river, the in-season MA is updated with more days of observed environmental conditions and estimated 50% dates from the Mission hydroacoustic facility.

MA models were developed on the underlying biological assumption of a link between an extreme river environment and increased en route fish mortality. The current temperature and discharge information used to produce the DBE forecasts is assumed to reflect the environmental conditions which ultimately influence the mortality of the incoming run. However, these models do not account for the length or shape of the run distributions. If the data used to construct the current MA models does not reflect the true shape and timing of the incoming run, then the environmental forecasts used to generate the MAs may not accurately reflect the true conditions experienced by the migrants. If the relationship between environmental exposure and fish mortality drives the observed DBEs, we hypothesise that the use of environmental averages weighted by the proportion of the daily incoming run will produce more accurate DBE forecasts than the 31-day symmetric or 19-day asymmetric un-weighted means. However, if MA predictions are robust to variability introduced by changes to run timing and/or run shape, then the current models may be a sufficient, and simpler, means of forecasting management adjustments.

The purpose of this report is to determine whether the development of a more biologically realistic model which explicitly incorporates run distribution information, and the corresponding uncertainty in run timing and distribution forecasts, will enable fisheries managers to increase the accuracy of DBE predictions, thereby increasing the probability of achieving sockeye salmon escapement targets. Three main objectives were identified in order to evaluate our hypothesis that the use of biologically realistic environmental averages will improve DBE forecasting capabilities: 1) evaluate annual Mission run distributions to determine whether 31-day symmetric and/or 19-day asymmetric models robustly capture the annual variation in run shape and length, 2) test the sensitivity of the MA predictions to changes in run shape, run timing and combined changes in run timing and shape (hereafter referred to as changes in run profile), and 3) examine the effect of incorporating run timing, run shape and run profile variability on the magnitude and precision of MA predictions.

METHODS

RUN PROFILE VARIABILITY

Run profile distributions estimated from data collected at the PSC hydroacoustic facility near Mission, BC since 1977 (Woodey 1987) were evaluated for the four major Fraser sockeye run timing groups (Early Stuart, Early Summer (omitting Pitt sockeye), Summer, and Late (omitting Birkenhead sockeye)). The Pitt population is omitted from the MA model as these fish do not pass the Mission hydroacoustic facility, and therefore do not contribute to the observed DBEs. Birkenhead fish are omitted from the Late-run analysis because they do not demonstrate the same historic migration delays which typified Late-run fish prior to the mid-1990s. Run length (number of days for which fish are observed entering the river), symmetry (distribution around the 50% date) and shape (shape of the daily count estimate distribution) were assessed and compared to the current 31-day and 19-day MA model structures. Symmetry was evaluated by calculating the number of days the run was observed at Mission on either side of the Mission 50% date, and the calculation of a skewness statistic (Zar 1996). The assumption that an *x*-day time frame adequately captures run conditions was evaluated by determining the proportion of each run contained within an *x*-day period surrounding the 50% date. The shape of the run profiles was evaluated using normality test statistics (skewness, kurtosis, Shapiro-Wilks test), a visual assessment of profiles, and estimation of best-fit model parameters (see below).

RUN DISTRIBUTION MODEL FITTING PROCEDURE

Model fit procedures were used to identify the best model, on average, for describing the shape of the run distributions. Evaluation of model fit provided further evidence of whether run profiles were symmetrically distributed and also parameterised models for use in simulating smoothed annual run distributions during sensitivity and uncertainty analyses (described below).

Given the large scatter observed for most of the run distributions, a 5-day moving average was initially used to smooth the annual data before model fitting procedures were applied. The fit of four different model distributions to the annual run profiles was assessed: normal, log normal, gamma and mixed normal. Forecasted daily run counts ($\hat{C}_i$) using the mixed normal model were calculated using Equation 3 (Holt and Cox 2007):

Eq. 3

$$F(\hat{C}_i \mid T, x, \overline{D}, k, \sigma_1, \sigma_2, p) = T * \left[p * \int_{i=0}^{x} \left(\frac{1}{\sigma_1 \sqrt{2\pi}} \right) * e^{\left(-\frac{(\overline{D} - D_i)^2}{2\sigma_1^2} \right)} di + (1 - p) * \int_{i=0}^{x} \left(\frac{1}{\sigma_2 \sqrt{2\pi}} \right) * e^{\left(-\frac{(\overline{D} + k - D_i)^2}{2\sigma_2^2} \right)} di \right]$$

where *T* is the total run size used to scale the model, *p* is a proportional scalar to weight the two distributions, D_i are the dates the run is observed at Hells Gate, $\overline{D}$ is the mean date associated with the first distribution, k is an adjustment term used to calculate the mean of the second distribution and σ_1 and σ_2 are the standard deviations of the first and second curve, respectively. The mixed normal model was evaluated as a potential descriptor of sockeye run shape data because it has the capacity to capture bimodal and skewed distributions and was demonstrated to perform well when applied to coho salmon (*Oncorhynchus kisutch*) escapement count data (Holt and Cox 2007). Numerical methods were used for best-fit parameter estimation using a Nelder-Mead algorithm procedure in the statistical software package R (http://cran.r-project.org/). The maximum likelihood estimation procedure selected parameters for each model that minimised the sums of squares. Model optimisation in R requires that initial (starting) parameters be provided to the estimation algorithm. Normal and log normal starting parameters were set to mean = 20 and standard deviation = 10. Gamma starting parameters were set to rate = 0.7 and shape = 12. Preliminary analyses revealed that the mixed normal model parameter optimisation was sensitive to initialisation values. This sensitivity was addressed by varying the initialisation parameters for each curve by using the mean of the best-fit normal distribution as the starting value for the mean of the first curve for the mixed normal model. The remaining initialisation parameters were held constant over all profiles and were: $k = 10$, $\sigma_1 = 2$, $\sigma_2 = 2$, and $p = 0.5$. Parameters for all models, with the exception of the p value for the mixed normal, were log transformed to constrain the optimisation search over a positive range. The mixed normal p value was logit transformed to constrain the search between values of 0 and 1.

Relative model fit was assessed using Akaike's Information Criterion (AIC; Eq. 4), where SS is the sums of squares, m is the total number of parameters in the model and n is the total number of observations. The model that produced the minimum AIC value for the majority of years for a given run group was then used to simulate smoothed annual daily run sizes for subsequent sensitivity and uncertainty analyses.

Eq. 4
$$AIC = \ln(SS) + \frac{2m}{n}$$

SENSITIVITY ANALYSIS

The first objective of the sensitivity analysis was to assess the change in the fit of the run-specific MA models (measured by changes in adjusted r^2 values) under several different scenarios representing different methods for calculating the average river temperature and discharge data:

varying number of days used to calculate the un-weighted average environmental conditions

asymmetric vs. symmetric environmental averages around the 50% Hells Gate date

averages weighted by the proportion of the run passing Hells Gate on a given day

only using data from years with extreme high temperature and discharge conditions

For consistency among run groups, the current MA model described by Equation 1 was used to model escapement discrepancies for all four run timing groups, including the Late-run. Temperature data was extracted from a historic database compiled from data collected at Hells Gate and Qualark since 1941 (Patterson et al. 2007b). Discharge data has been recorded at Hope since 1912 and was extracted from an online database maintained by the Environment Canada Water Survey of Canada Program (http://www.wsc.ec.gc.ca/). In order to calculate the weighted environmental averages, five days were added to the Mission run distribution data to account for the average lag time caused by up-river migration to Hells Gate (English et al. 2003; English et al. 2004; English et al. 2005; Robichaud and English 2006). Late-run distributions in certain years were truncated to accommodate the available temperature dataset.

For the second objective, we assessed the robustness of MA model predictions to changes in 50% date, run shape, and run profile over a range of environmental scenarios represented by different years of observed temperature and discharge conditions. Sensitivity to 50% date was evaluated for both 31-day symmetric and 19-day asymmetric models, as well as for weighted average models. In addition, sensitivity to run shape and run profile (changes to both 50% date and the shape of the run distribution) were evaluated for the weighted average models. A subset of environmental data from 1995 – 2006 was used to represent several environmental scenarios, as this time frame incorporates a mixture of extreme and moderate environmental conditions. For each environmental scenario year, escapement discrepancies were predicted from the Equation 1 MA model using run-group specific run timing and run shape data from 1977 – 2004 (see Appendix B). Although available, 2005 run timing and run shape observations were not included as 2005 represents an extreme outlier for these variables (I. Guthrie, PSC, pers. comm. 2006). For the weighted average run shape (50% date held constant) and run timing (run shape held constant) analyses, the static (constant) variable was set to match the value observed during the environmental scenario year (e.g. if 1995 environmental data was used, the 50% date or run shape for 1995 would be applied to run distributions from 1977 – 2004). The combined effect of run timing and run shape (referred to as the run profile sensitivity analysis) was captured by repeating the MA analysis for each year of environmental data using the observed timing and shape of each distribution from 1977 – 2004. MA model sensitivity to changes in each variable (run timing, run shape, or run profile) was measured using the standard deviation (SD) of MA predictions over all environmental scenarios (i.e. each year of environmental data). The analysis was repeated for all sockeye run timing groups with the exception of the Late-run. Because the historic temperature dataset often truncates before the end of most Late-run migrations, only limited Late-run sensitivity analyses could be completed.

UNCERTAINTY ANALYSIS

The uncertainty analysis evaluated the incorporation of run timing, run shape and run profile uncertainties on the precision and accuracy of MA model predictions. Uncertainty analyses assumed ‘perfect knowledge’ of all other conditions excluding 50% date, run shape or run profile (i.e. run timing, run shape and run profile uncertainty were incorporated in isolation from any other uncertain states of nature; e.g. using observed environmental data and no error in the MA model).

Two different methods were explored for simulating 50% date uncertainty: a non-parametric bootstrap of historic 50% dates and the error structure generated from an oceanographic 50% date forecasting model (described in Appendix C). The oceanographic method was only applied to data for the Early Stuart run. For the Early Stuart run, the value of incorporating 50% date uncertainty using the oceanographic model was quantified by comparing the median of the MA uncertainty distributions to the point-value MA calculated using the mean 50% date forecast from the oceanographic model (i.e. no 50% date uncertainty).

As previously mentioned, run distributions were simulated using identified best-fit models to smooth out daily variability. Run shape uncertainty was simulated using a non-parametric bootstrap of historic run distributions shifted to have a 50% date equivalent to the median historic 50% date for each run group (Early Stuart = July 14; Early Summer = August 11; Summer = August 18). Run profile uncertainty (incorporating changes to both the shape and timing of the run) was simulated using a non-parametric bootstrap of historic distributions, retaining the observed 50% date associated with the distribution for each year.

The data from 500 bootstrapped 50% dates, run shapes, or run profiles generated from 1977-2004 Mission hydroacoustic estimates was used to extract 500 observed temperature and discharge averages for each year ranging from 1995 – 2006 (31-day symmetric averages for the 50% date analysis and weighted averages for the run shape and run profile analyses). Corresponding MAs were then predicted using Equation 1 for each set of bootstrapped values to create a range of MA predictions associated with each year of environmental data. The median MA values from the predicted distributions were then compared to the annual observed 'true' discrepancies calculated from observed lower-river and up-river escapement estimates, and sums of squares were computed. Finally, the sums of squares between models incorporating run timing vs. run shape vs. run profile uncertainty were compared relative to one another. Simulations were repeated for Early Stuart, Early Summer and Summer-run groups.

RESULTS

RUN PROFILE VARIABILITY

Summaries of run distribution characteristics for each sockeye run group are provided in Table 1. Year-specific results are presented in Appendix A – Historic run profiles, Tables A1 - A4). Run distributions demonstrated asymmetry in almost every year for all four run groups. There was no pattern to the direction of the skew for Early Stuart or Summer-runs, but the Early Summer and Late-run distributions exhibited more days of river entry *before* 50% of fish had entered the river than were observed *after* the first half of the run had passed Mission (i.e. distributions of date by daily fish estimation were left skewed). On average, Early Stuart-runs enter the river for 33.8 days (range: 21-45 days), Early Summer-runs 52.0 days (range: 35-85 days), Summer-runs 62.6 days (range: 40-85 days), and Late-runs 45.7 days (range: 30-79 days). Approximately 90% of the fish in each run were included in a 31-day symmetric period centered on the Hells Gate 50% date (Early Stuart = 98%; Early Summer = 90%; Summer = 89%; Late = 90%). However, for the short Early Stuart-run, a 31-day period often encompassed days on either side of the run distribution, and for the Late-run this time frame often included days after the end of the run (Table 1). In other words, the use of a 31-day mean sometimes included temperature and discharge values not actually experienced by these runs at Hells Gate, but while the fish were at locations further down- or upstream.

For all groups, there were several years during which the run distribution was distinctly bi- or multi-modal and most distributions were non-normal (i.e. few distributions had a non-significant Shapiro-Wilks normality test statistic) (Table 1). In Appendix B - Run profile model fitting, figures B1 - B4 illustrate daily Mission hydroacoustic estimates for each run group from 1977 - 2005, smoothed with a 5-day moving average (to smooth out some of the daily variability) and plotted with the best-fit mixed normal curves. Appendix B also includes summary tables describing the model fitting results for each run group. The mixed normal model provided the best fit to the data as it captured the skewness, kurtosis, and bi-modality present in many of the datasets; the few exceptions are described in Appendix B tables. Based on the success of the mixed normal model performance, subsequent run shape and run profile analyses were completed using the best mixed-normal fits to observed daily run size estimates to represent the annual run distribution for each group.

Preliminary analyses evaluated several potential predictor variables for the best-fit migration profile model parameters for each group. Variables included: indices of run size, run timing and temperature exposure, and cycle year. However, no single variable was found which significantly, and consistently, predicted all run profile model variables (Hague unpub. data). Cycle year was the most consistent predictor for Early Stuart and Early Summer migration profiles (predicted three of the mixed normal model parameters at a 0.1 significance level), but did not significantly predict any Summer run profile characteristics (Hague unpub. data).

Therefore, sensitivity and uncertainty analyses bootstrapped the entire historic run distribution dataset as there was no clear method to predict the shape or timing of the run in each year.

SENSITIVITY ANALYSIS

MA model fit

Table 2 presents results of the sensitivity of MA model fit to changes in run timing and run distribution parameters. There was a general trend towards increased model-fit (higher adjusted r^2 value) using a greater number of days to increase the mean environmental conditions. A 31-day mean produced the best-fit to Summer-run data, while the Early Stuart and Early Summer data were best fit using a 45-day asymmetric mean. The use of symmetric (e.g. 9-9; 15-15; 22-22 days), as opposed to asymmetric (e.g. 15-3; 20-10; 30-14 days), environmental means also trended towards improved MA model-fits for all run groups (Table 2). It is important to note that no assumptions were made with regards to missing data values, which were predominantly found in June and early July temperature data, thus primarily influencing the fit of the Early Stuart models. This issue may explain the improvement to models with equal or heavier weighting on later dates (i.e. fewer missing values). Replacing missing values using historic daily average temperatures, or interpolations from available data, may result in a historic dataset which produces a different MA relationship, and is an issue which should be carefully considered during future analyses. The decreased performance of the asymmetric models illustrates the limitations associated with predicting in-season management adjustments, where forecasting and management restrictions currently compel the use of 19-day asymmetric environmental averages.

The performance of the weighted average models was varied (Table 2), which was in contrast to our original hypothesis that the creation of more ‘biologically relevant’ temperature and discharge models would improve the performance of the current MA models. Historic weighted temperature and discharge averages provided a better fit to historic MA data than 19-day asymmetric averages for all groups with the exception of the Late-run. However, 31-day symmetric averages provided a better fit to Early Stuart and Early Summer data, and a comparable fit to Summer data, than the weighted averages. In summary, the weighted average models provided a better fit to historic MA data compared to the current 19-day asymmetric in-season models, but a poorer fit than the 31-day symmetric pre-season models.

MA model forecast sensitivity

The sensitivity of MA forecasts to changes in run timing, run shape and run profiles varied across run groups, and across different temperature-discharge scenarios (Figures 2 – 7). Figures 3, 5 and 7 compare the sensitivity of 31-day symmetric and 19-day asymmetric models to changes in 50% date. The Early Stuart 19-day model was slightly more robust to changes in run timing than the 31-day model, while the opposite result was observed for the Early Summer and Summer runs (31-day model had smaller standard deviations in more years).

For all run-groups, weighted MA forecasts were more sensitive to changes in run timing than to changes in the shape of the run distribution (Figures 2, 4, 6). In slightly more than half of the scenarios, the combined effect of altering both run shape and run timing (i.e. run profile), produced more variability than changes in run timing alone. The Early Stuart model results were the most sensitive, on average, to changes in timing, shape, and profile (Figure 2) while the Early Summer and Summer models were less sensitive (Figure 4 and 6). When comparing the standard deviations of MAs predicted using the weighted, 31-day, or 19-day environmental averages, results were highly variable and no single model consistently displayed the lowest SD across all years of environmental data.

The relative sensitivity of the MA models to changes in run timing and/or shape for a given set of environmental conditions was correlated to the degree of temperature variability within the historic migration window for each run for a particular year (compare Figures 2-7 and Figure 8) (i.e. high SD in temperature values was correlated to high SD in MA predictions over a range of run timing or run shape conditions). For example, in 1998, the historic Early Stuart migration period (July 8 – July 21 Hells Gate 50% dates) bounded a period of rapidly changing temperature conditions. However, for the same year, over the time period of historic Early Summer migrations (July 27 – Aug 15 Hells Gate 50% dates), temperatures were relatively constant. As a result, years with high MA sensitivity for one run group may not correspond to high MA sensitivity for another run group. Annual discharge trends are relatively smooth; therefore, appear unlikely to contribute significantly to changes in MA sensitivity except in years when there is a period of rapid discharge change during the summer (i.e. caused by a major rainfall event (e.g. 1999; Figure 9)).

In years with low MA forecast variability, the 31-day mean and weighted mean forecasts for the Early Stuart-run (Figures 2 and 3) were quite similar (e.g. 1995 – 1997; 2000 – 2002; 2005). Differences in model predictions were more apparent in years where the MA model was sensitive to changes in run timing and/or shape (e.g. 1998; 1999; 2004; 2006). The weighted and un-weighted models produced similar forecasts for all the Early Summer-run scenarios (Figures 4 and 5) and for the majority of the Summer-run scenarios, with the exception of 2004 (Figures 6 and 7). The similarity between MA predictions under changing run timing and run profile conditions indicates that MA forecasts under different run profile scenarios were more strongly influenced by associated changes to run timing than by changes to run shape.

<u>Uncertainty analysis</u>

For the Early Stuart data, the sums of squares (*ss*) between the observed MA values and the median of the MA distribution forecasted from the range of 50% dates generated by the oceanographic model was smaller than the *ss* between the observed MAs and the discrete MA values forecasted from the mean predicted 50% date (Figure 11). These results suggest that, on average, there is a benefit to incorporating the 50% date uncertainty from the oceanographic forecast model into MA predictions. However, the benefit of including run timing uncertainty was greatly reduced if 1998 (a high temperature year) was removed from the analysis. The high variance in the 1998 MA forecasts occurs because of the large variability in observed temperature associated over the range of 50% dates predicted by the oceanographic Early Stuart model for this year (Figure 8). In addition, simulating 50% date uncertainty using the oceanographic model (Figure 11; *ss* = 1.97) produced only moderate improvements to the sums of squares compared to simulating 50% date uncertainty using the historic bootstrap method (Figure 11; *ss* = 2.03). These results suggest that the large uncertainty in the relationship between historic oceanographic conditions and run timing may limit the forecasting power of the oceanographic model.

For all remaining analyses, the sums of squares for the different uncertainty models were simply compared relative to one another. The sums of squares for the Early Stuart historic 50% date bootstrap model (*ss* = 2.03) was less than the sums of squares for the uncertain run shape (*ss* = 2.29) or run profile (*ss* = 2.52) MA models (Figure 12). The superior performance of the 31-day 50% date model supports the model fit results described in Table 1. The smaller *ss* for the run shape model than for the run profile model suggests that the performance of the Early Stuart weighted average MA model actually improves if uncertainty in 50% date is ignored and the historic median 50% date is used as the 50% date for all run distributions. For the Early

Summer-run data, the sums of squares for the run timing (*ss* = 1.20) and run shape (*ss* = 1.18) uncertainty models were comparable (Figure 13). However, as with the Early Stuart models, the incorporation of run profile uncertainty (*ss* = 1.33) weakened the relative fit to historic MA values. Unlike the earlier run-timing groups, the Summer run shape uncertainty model produced a smaller sums of squares (*ss* = 0.69) between observed and median predicted MA values than did the historic 50% date bootstrap model (*ss* = 0.78). Similar to the Early Stuart and Early Summer run groups, the incorporation of run profile uncertainty also reduced the fit to observed MA values (*ss* = 0.75).

For all groups, years with high average temperatures and/or discharges were associated with more uncertainty in the forecasted MA distribution. This effect occurs because extreme temperature and/or discharge years also tend to be associated with more variable environmental conditions (Figures 8 and 9) and increased variability in environmental conditions translate, on average, into larger variability in MA forecasts. This trend was also observed during the sensitivity analysis (Figures 2 - 7).

DISCUSSION

RUN PROFILE VARIABILITY

Our first objective evaluated whether the simple averages used to calculate environmental conditions for the current MA models accurately reflect the true shape and timing of the incoming sockeye run. Although we found significant variability in both run length and distribution shape, there are several reasons why simple environmental averages may provide a better fit to historic DBEs than weighted averages. The first explanation involves the various sources of input which contribute to the discrepancy. DBEs are influenced not only by environmentally-induced mortality events but also by factors unrelated to fish health such as estimation and observation errors and unrecorded in-river catches. A simple 31-day average may remove more of the inter- and intra-annual variation in the numerous sources contributing to the overall DBE, as opposed to the weighted average model which focuses on explaining only the environmental component. The second explanation requires closer consideration of what constitutes the ‘true’ migration conditions experienced by a run. The weighted average models capture the conditions experienced by a group of fish at one location in the river for a given day. These fish are in the system for multiple days and are exposed to a broader range of temperature and discharge conditions than those they face at Hells Gate on a single day. In addition, fish are generally in the system for a longer time after they pass Hells Gate than before it; therefore, the models implicitly weight the river conditions present during the early portion of the migration more heavily. Despite our original hypotheses, the weighted models may not, in fact, reflect more ‘biologically relevant’ environmental exposures. More research into the development of a multi-site cumulative exposure model may lead to improved estimates of the true environmental exposures experienced by each run group.

In years characterised by extreme temperature and/or discharge conditions, large DBEs are thought to be primarily caused by environmentally induced natural mortality (Macdonald et al. 2000; Patterson et al. 2007a). Therefore, we were not surprised to observe improved MA model fit using only data from high temperature and discharge years. However, it is unclear how well an extreme-year model would predict DBEs in average-condition years. The limited number of extreme data years, and the associated limits to the range of data used to fit the model, would increase the frequency of curve extrapolations, thus increasing forecast uncertainty. A robust retrospective analysis of different MA models should be applied to determine whether it is advantageous to apply different model structures in high temperature and/or high discharge years. Until a more rigorous evaluation is applied, we recommend continued use of the full suite of environmental data.

Sensitivity analysis

Our results illustrate that although MA forecasts are relatively robust to changes in the shape of the incoming run distribution, errors in run timing estimation can produce biased DBE estimates. Timing sensitivity reflects the seasonal variability in the magnitude and precision of environmental forecasts (Patterson and Hague 2007) and is a concern for sockeye salmon managers. River entry timing is difficult to predict, as illustrated by the variability in the Early Stuart oceanographic model. In the case of Late-run fish, scientists are still struggling to explain a sudden and dramatic change in river-entry timing that first occurred in the mid-1990's (Lapointe et al. 2003; Cooke et al. 2004). Previously, Late-run sockeye exhibited a unique holding pattern in the Strait of Georgia; however, a large percentage of the Late-run now enters the Fraser River immediately upon arrival and is thus exposed to warmer and higher flow river conditions for an extended period of time. This shift caused severe increases in the observed escapement discrepancies and initiated the development of a run-timing based MA model which is typically used for Late-run discrepancy forecasts.

MA model sensitivity to changes in 50% date is not uniform. The implications of an error in forecasted 50% date will vary both annually and seasonally. For example, previous studies have discovered that long range temperature forecasts are relatively insensitive to changes in 50% date in the region of the historic temperature plateau (Patterson and Hague 2007; Figure 10). The Early Stuart run typically enters the river on the ascending limb of the thermograph, and DBE forecasts for this group are the most sensitive to changes in run timing and/or run shape. Conversely, because the Early Summer and Summer migration periods roughly coincide with the historic thermograph plateau, MA models for these runs are more robust to errors in run timing or shape estimation. The temporal shift in the precision of the forecasted DBE will also be influenced by the seasonal changes in the performance of the environmental forecasting models. Both pre- and in-season environmental forecasts become less certain over longer range forecasting periods (Morrison 2005; Morrison and Foreman 2005; Patterson and Hague 2007). Finally, we observed an increase in MA model sensitivity during years with extreme high temperature and discharge conditions, because these years are often associated with more periods of rapid change in the thermographs, and hydrographs, respectively (Figures 8 and 9).

Uncertainty analysis

With the exception of the use of the oceanographic 50% date forecasting model for the Early Stuart uncertainty analysis, it is currently difficult to explicitly quantify the effect of including run timing, shape and profile uncertainty on the average accuracy of MA forecasts. To do so would require parallel methods for producing point value forecasts for comparison. Our analyses did show slight improvements to the accuracy of DBE predictions if 50% date uncertainty is ignored. However, we omitted several other sources of pre-season and in-season forecast uncertainty in our analysis. For example, weighted average models require pre-season forecasts of daily, as opposed to average, temperature and discharge values. Long-range forecasts of daily environmental conditions are highly uncertain (Patterson and Hague 2007) and would likely eliminate the small increases in precision observed with the use of a weighted average pre-season MA model incorporating run shape uncertainty.

Recommendations

The selection of the most appropriate MA model for sockeye salmon management involves the evaluation of trade-offs between biological relevance, model fit, uncertainty in predictor variables, the robustness of the model to forecast uncertainty, and general forecasting limitations. We evaluated our results to compile several recommendations for researchers seeking to apply MA models.

Our first recommendation is continued use of an un-weighted 31-day mean pre-season MA model for all four run groups for three reasons. First, the fit of most MA models improves when a longer time frame is used to calculate the environmental mean. Second, 31-day un-weighted environmental averages improve the fit to historic DBEs over the use of weighted averages. Finally, we are currently restricted by our limited capacity to accurately forecast the daily environmental conditions required for weighted pre-season MA forecasting models.

Our second recommendation is to remove the restraints requiring the current application of an in-season 19-day asymmetric MA model. Sensitivity analyses demonstrated a significant loss in model fit for 19-day asymmetric compared to 31-day symmetric and weighted average models. Two main limitations necessitate the shorter, asymmetric time-frame for in-season MA forecasts: 1) the decreased accuracy of long range daily environmental forecasts (e.g. the accuracy sharply decreases for forecasts longer than ~ 10 days; Morrison 2005), and 2) the delay in updates of 50% date forecasts. Researchers could address the first limitation by considering an alternative in-season environmental forecasting model using the historic relationship between conditions on different dates (Patterson and Hague unpub. data). Currently, 50% date forecasts are updated using information for test fisheries located in Juan de Fuca and Johnstone Straits. Earlier, albeit less accurate, 50% date forecasts could be facilitated by utilizing more seaward test fisheries. Alternatively, researchers may want to consider an alternative management structure where multiple in-season MA updates are provided – with a trade-off of more uncertainty associated with the earlier forecasts (David Patterson, DFO, pers. comm. 2006). For example, an in-season forecasting method which blends forecasts of environmental conditions based on the historic relationship between temperature and discharge and the current 10-day forecast method for different points in the season, as discussed above, (Patterson and Hague unpub. data) could be used to provide updated MA estimates, with increasing precision as the season progresses.

Our third recommendation is to explore the benefit of incorporating run timing uncertainty into MA model forecasts, either directly or through consideration of sensitivity analysis outputs. It is important for sockeye salmon researchers to consider the implications of run timing errors on DBE forecasts, particularly given the difficulties in accurately forecasting Hells Gate 50% dates and the recent, inexplicable, shift in Late-run entry timing (Lapointe et al. 2003; Cooke et al. 2004). In general, river temperature is more likely to be sensitive to a temporal shift in the time-range associated with the ascending or descending limb of the historic thermograph. In the case of sockeye salmon, this translates into increased sensitivity for Early Stuart run data and decreased sensitivity for Early Summer and Summer-runs. Increased sensitivity is also more likely to occur in extreme temperature and/or discharge years, where sudden fluctuations in river conditions are more common. Although researchers do not have the capacity to accurately predict small-scale environmental changes, they can apply the above generalisations to better reflect the effect of timing uncertainty on their results. One option is to incorporate 50% date uncertainty into environmental and MA forecast models, which produced modest improvements to retrospective Early Stuart MA predictions evaluated in this study. The second option is to consider the sensitivity of MA models to changes in the average historic summer river temperature and discharge conditions experienced by each run group. Scientists can assist managers by providing annual DBE forecasts for a range of predicted temperature and discharge conditions. Managers can then easily ascertain, on average, how sensitive the prediction associated with a specific date and/or group might be to changes in arrival timing. However, managers should still be aware that any of the generalizations with regards to run group or extreme vs. moderate condition years could easily be violated during a periods of sudden and unexpected environmental change.

In conclusion, given the relatively good fit of un-weighted environmental averages compared to historic sockeye escapement discrepancies, and the large uncertainty associated with predictions of run profile and daily environmental conditions, simple un-weighted models may currently be the preferred method for forecasting pre- and in-season MAs. Future research should continue to explore alternative methods for capturing the true nature of the relationship between escapement discrepancies and environmental conditions. One alternative approach is the consideration of cumulative exposure models. A second approach is the development of a strictly mortality-based model with observation and implementation error added as variability around a predicted level of salmon mortality. Our analyses only considered one structural MA model (Eq. 1); however, the methods we described should be applied as part of a rigorous assessment package for the evaluation of alternative model structures. Given the wide range of variables contributing to management adjustments, and the uncertainty associated with the numerous model inputs, it will be unrealistic to develop perfect MA forecasts. However, by taking the uncertainties into account and developing models that best represent the underlying conditions contributing to the annual DBEs, we may be able to improve upon the average predictive performance of the current MA models, thus increasing the probability of achieving management objectives for the Fraser River sockeye fishery.

TABLES

Table 1. Summary of variability in run profile characteristics for Early Stuart, Early Summer, Summer and Late Fraser River sockeye salmon runs from years 1977 - 2006.

Distribution characteristics	**# left skew[1] years**	**# right skew[1] years**	**# bi/multi-modal years**	**Mean run length (days) (range)**	**% run captured by 31-day symmetric**	**% run captured by 19-day asymmetric[2]**	**Mean Mission escapement estimate**
Early Stuart	17	13	6	34 (21-45)	98	71	241 297
Early Summer	3	27	16	53 (35-85)	90	64	316 560
Summer	17	13	17	63 (40-85)	89	63	1 874 741
Lates	5	25	13	46 (30-79)	89	61	1 089 350

Notes: [1]left skew = more days after the 50% date; right skew = more days before the 50% date.
[2]19-asymmetric mean is 15-days before and 3-days after the 50% date.

Table 2. Change in management adjustment model fit (measured by adjusted r^2) using different methods to calculate average temperature and discharge predictor variables. Models were evaluated using either all years of historic MA data (All years; 1977 – 2005) or only years of extreme high temperature and discharge conditions (Extreme years; Table 6). The best-fit MA models for each run group are in bold. Given the limited historic temperature time series available, most Late-run models could not be re-constructed.

Model	**Early Stuart**		**Early Summer**		**Summer**		**Lates**	
	All years	*Extreme years*	*All years*	*Extreme years*	*All years*	*Extreme years*	*All years*	*Extreme years*
45-day symmetric	0.53	**0.56**	0.35	**0.61**	0.52	0.46	NA	NA
45-day asymmetric^{45A}	0.31	0.29	**0.44**	0.49	0.47	0.70	NA	NA
31-day symmetric	**0.57**	**0.56**	0.32	0.52	**0.56**	**0.95**	NA	NA
31-day asymmetric^{31A}	0.41	0.41	0.33	0.43	0.52	0.83	NA	NA
19-day symmetric	0.37	0.45	0.40	0.41	0.50	0.91	NA	NA
19-day asymmetric^{19A}	0.31	**0.56**	0.27	0.34	0.44	0.29	**0.90**	**0.96**
Weighted	0.44	0.47	0.28	0.49	**0.56**	**0.95**	0.83	0.86

Notes: 45A = 30 days before 50% date, 14 days after; 31A = 20 days before 50% date, 10 days after; 19A = 15 days before 50% date, 3 days after.

Table 3. Identification of extreme environmental condition years (high temperature, high discharge and/or extreme shift in run timing) based on a 19-day asymmetric (15-days before, 3-days after) mean period centred on the Hells Gate run timing date for each run group. Discharge conditions are as measured at Hope; temperature conditions are as measured at Qualark.

Early Stuart		Early Summer		Summer		Late	
Year	Extreme discharge (cms) or temperature (°C)	Year	Extreme discharge (cms) or temperature (°C)	Year	Extreme discharge (cms) or temperature (°C)	Year	Extreme run timing (Hells Gate 50% date)
1990	7248	1978	18.8	1979	18.0	1996	Sep 11
1991	6286	1982	5743	1981	18.1	1997	Sep 16
1992	17.9	1984	5979	1982	5602	1998	Sep 18
1994	15.1*	1990	19.8	1990	19.9	1999	Sep 14
1996	6727	1991	18.0	1992	19.6	2000	Aug 18
1997	7644	1992	19.8	1994	19.2	2001	Aug 25
1998	18.0	1994	19.4	1998	19.5	2002	Sep 17
1999	9347	1996	5450	1999	5780	2003	Sep 1
2000	7071	1997	6379	2003	18.9	2004	Aug 25
2002	7713	1998	20.4	2004	20.2		
2004	17.7	1999	7126				
		2000	5988				
		2001	5290				
		2003	19.4				
		2004	19.8				

Note: *Low mean, but later half of the run experienced temperatures >20°C, so still included as an extreme temperature year.

FIGURES

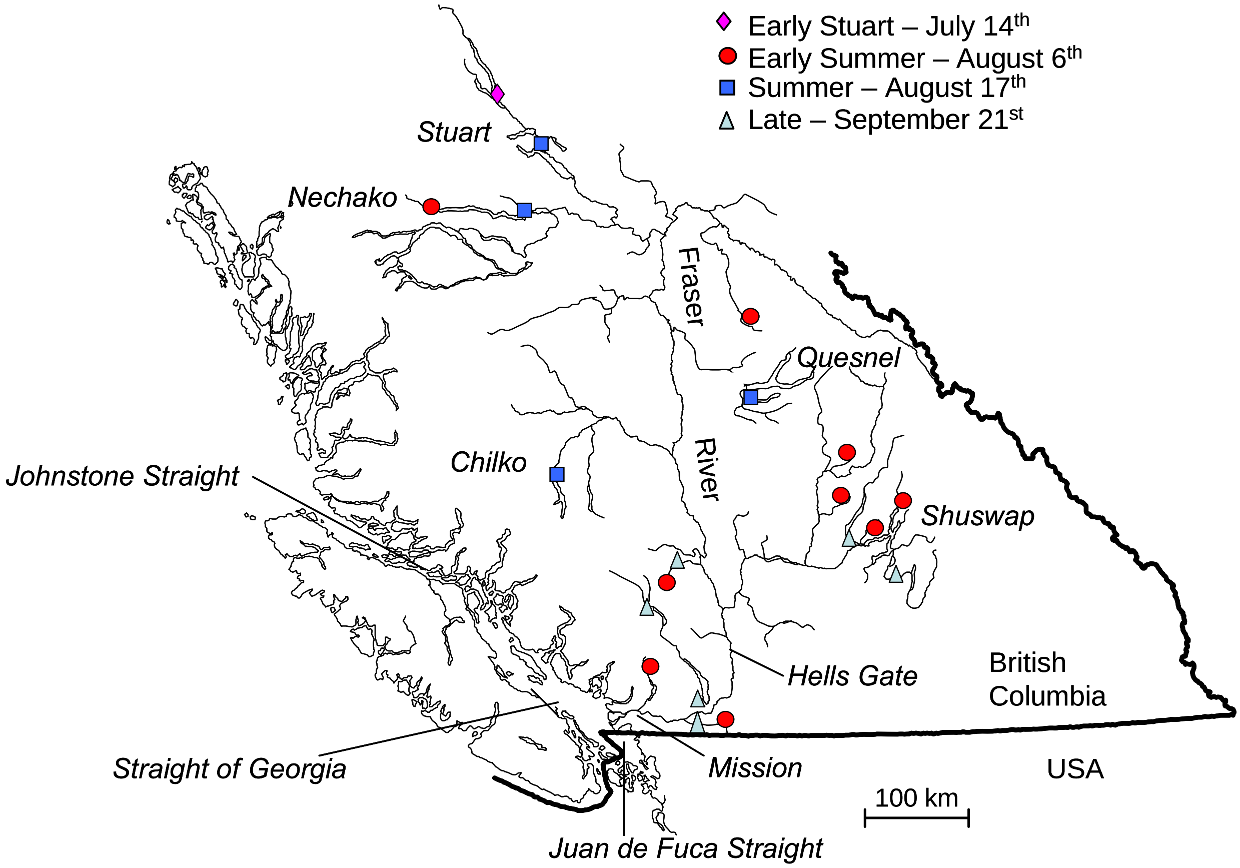

Figure 1. Map of Fraser River watershed and major Early Stuart, Early Summer and Summer spawning grounds and historic median Hells Gate 50% dates as indicated in the legend.

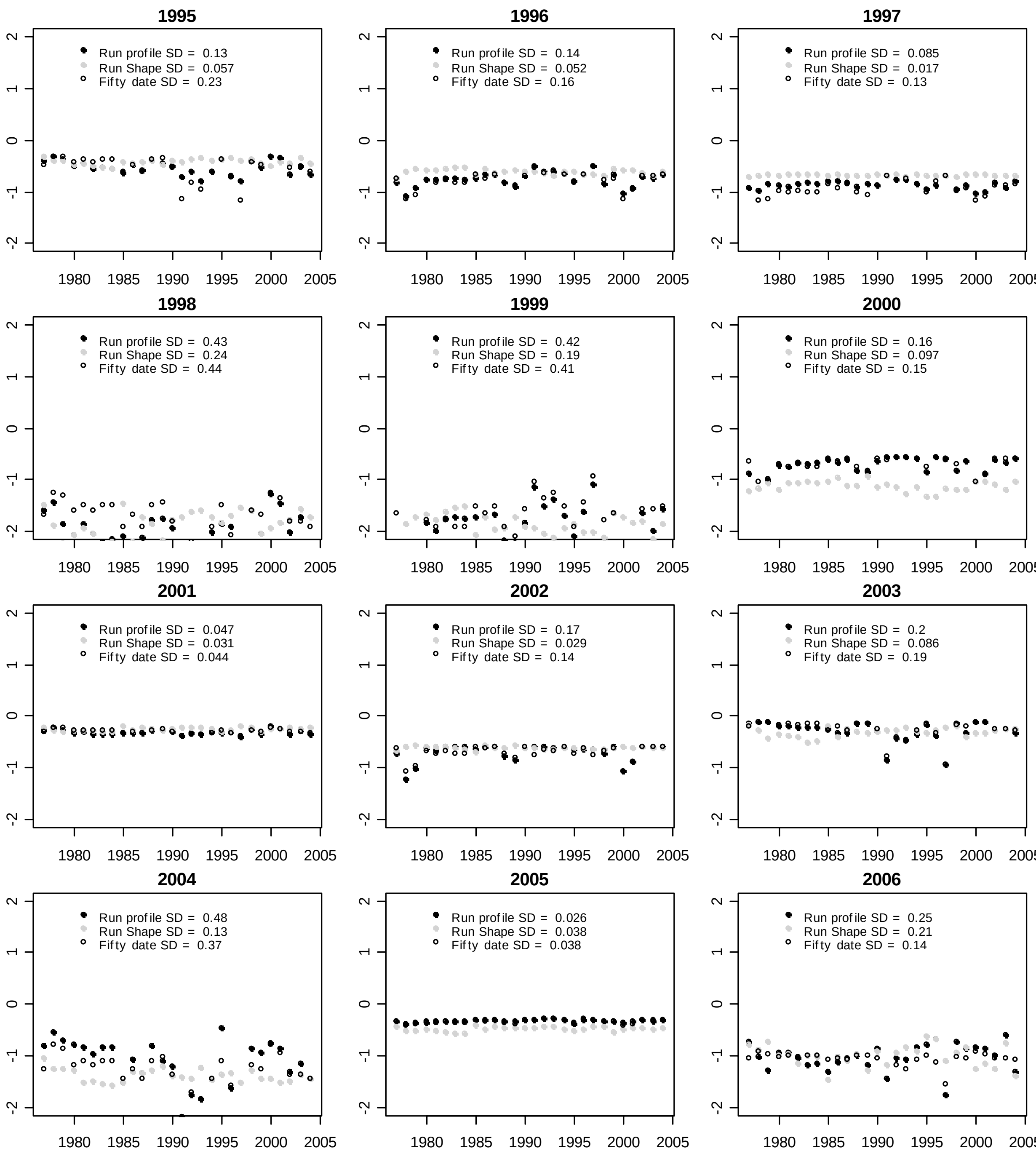

Figure 2. Sensitivity (SD) of Early Stuart weighted average MA model predictions (y-axis) to changes in 50% date (open points; constant run shape pertaining to the environmental scenario year), run shape (grey points; constant 50% date pertaining to the environmental scenario year), or run profile (black points; changes in both run shape and run timing) under different years of observed Fraser River temperature and discharge conditions (x-axis). Variability in run distribution parameters was represented using historic data from 1977 – 2004.

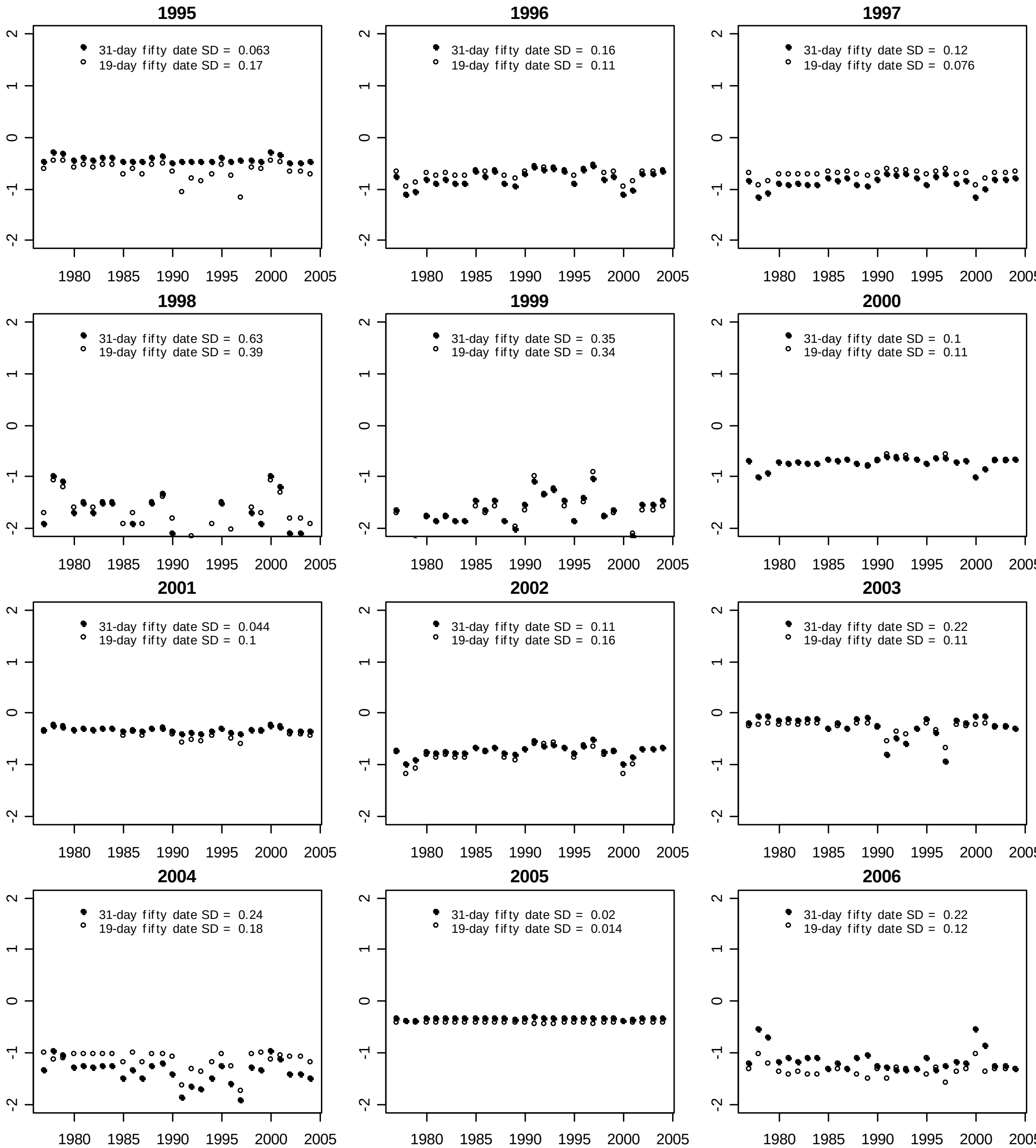

Figure 3. Sensitivity (SD) of Early Stuart 19-day asymmetric and 31-day symmetric MA model predictions (y-axis) to changes in 50% date (open points = 19-day asymmetric; closed points = 31-day symmetric) under different years of observed Fraser River temperature and discharge conditions (x-axis). Timing and profile variability was represented by historic values from 1977 – 2004.

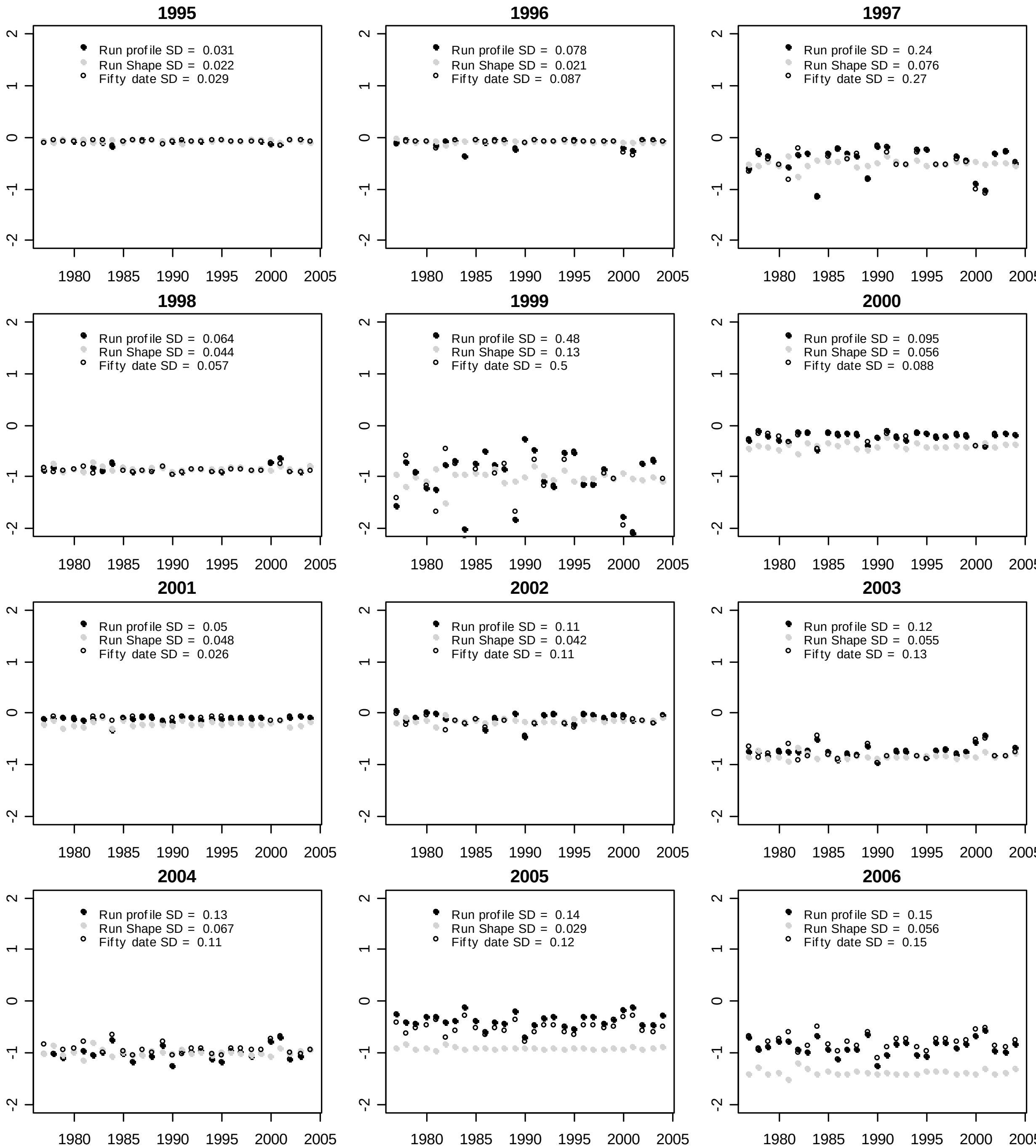

Figure 4. Sensitivity (SD) of Early Summer weighted average MA model predictions (y-axis) to changes in 50% date (open points; constant run shape pertaining to the environmental scenario year), run shape (grey points; constant 50% date pertaining to the environmental scenario year), or run profile (black points; changes in both run shape and run timing) under different years of observed Fraser River temperature and discharge conditions (x-axis). Variability in run distribution parameters was represented using historic data from 1977 – 2004.

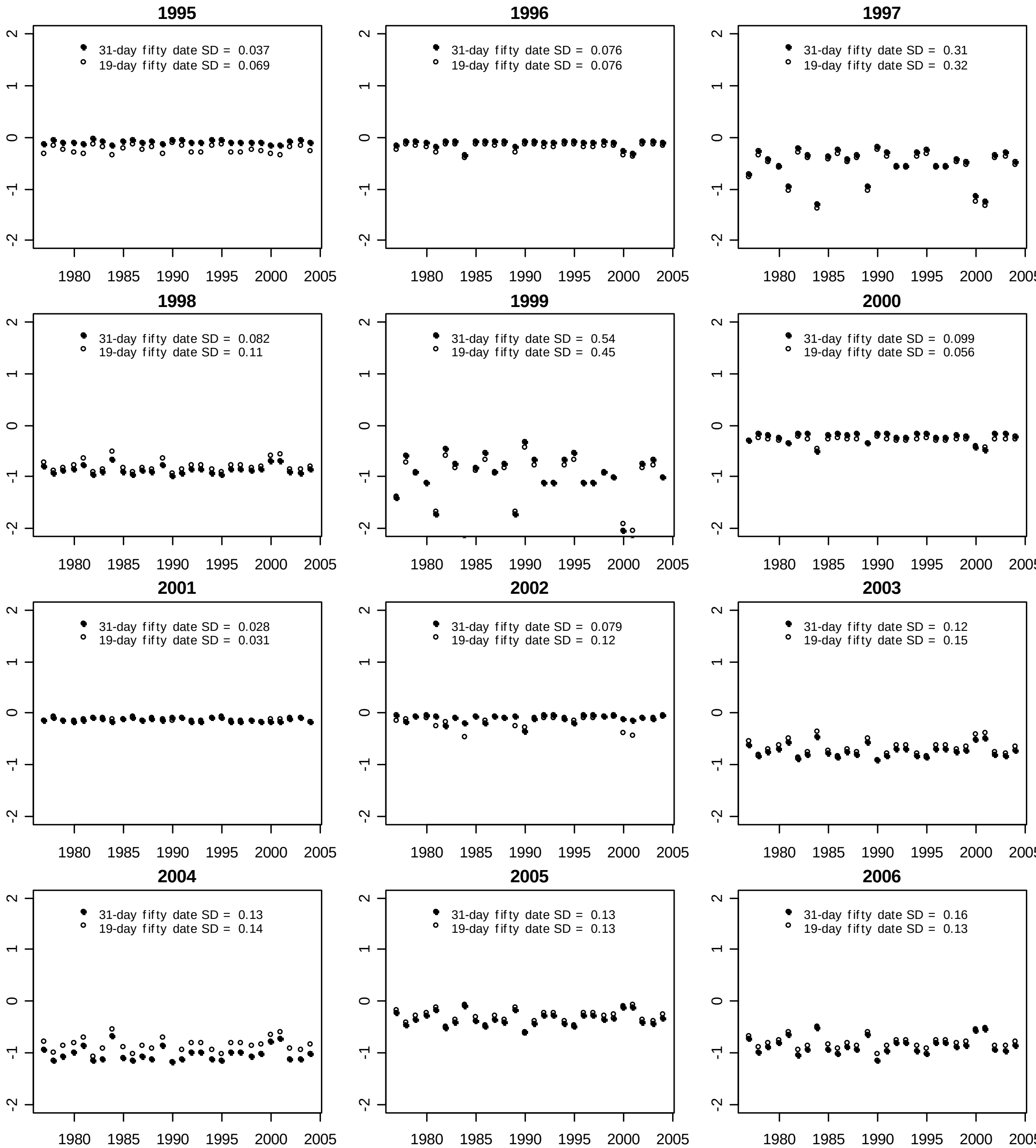

Figure 5. Sensitivity (SD) of Early Summer 19-day asymmetric and 31-day symmetric MA model predictions (y-axis) to changes in 50% date (open points = 19-day asymmetric; closed points = 31-day symmetric) under different years of observed Fraser River temperature and discharge conditions (x-axis). Timing and profile variability was represented by historic values from 1977 – 2004.

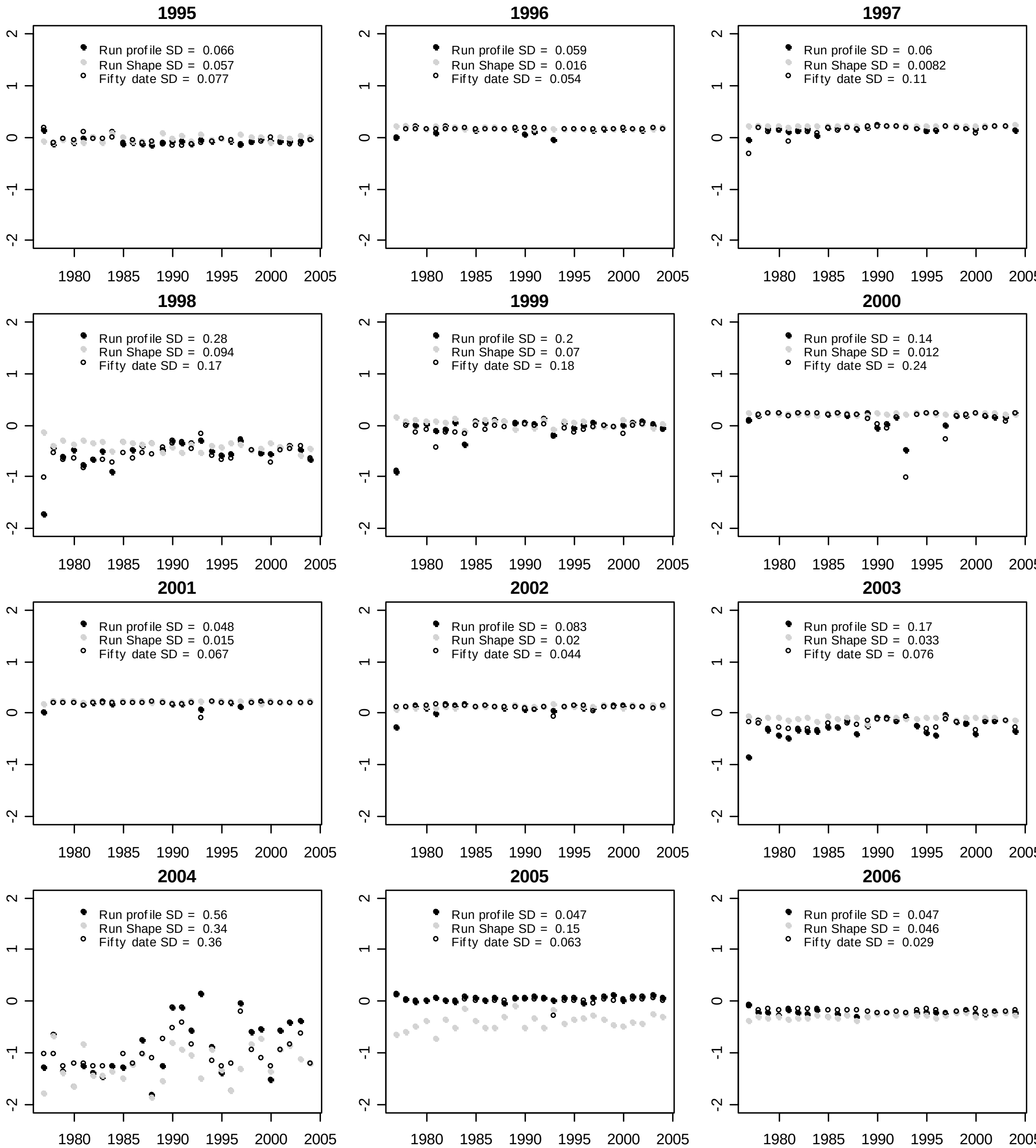

Figure 6. Sensitivity (SD) of Summer weighted average MA model predictions (y-axis) to changes in 50% date (open points; constant run shape pertaining to the environmental scenario year), run shape (grey points; constant 50% date pertaining to the environmental scenario year), or run profile (black points; changes in both run shape and run timing) under different years of observed Fraser River temperature and discharge conditions (x-axis). Variability in run distribution parameters was represented using historic data from 1977 – 2004.

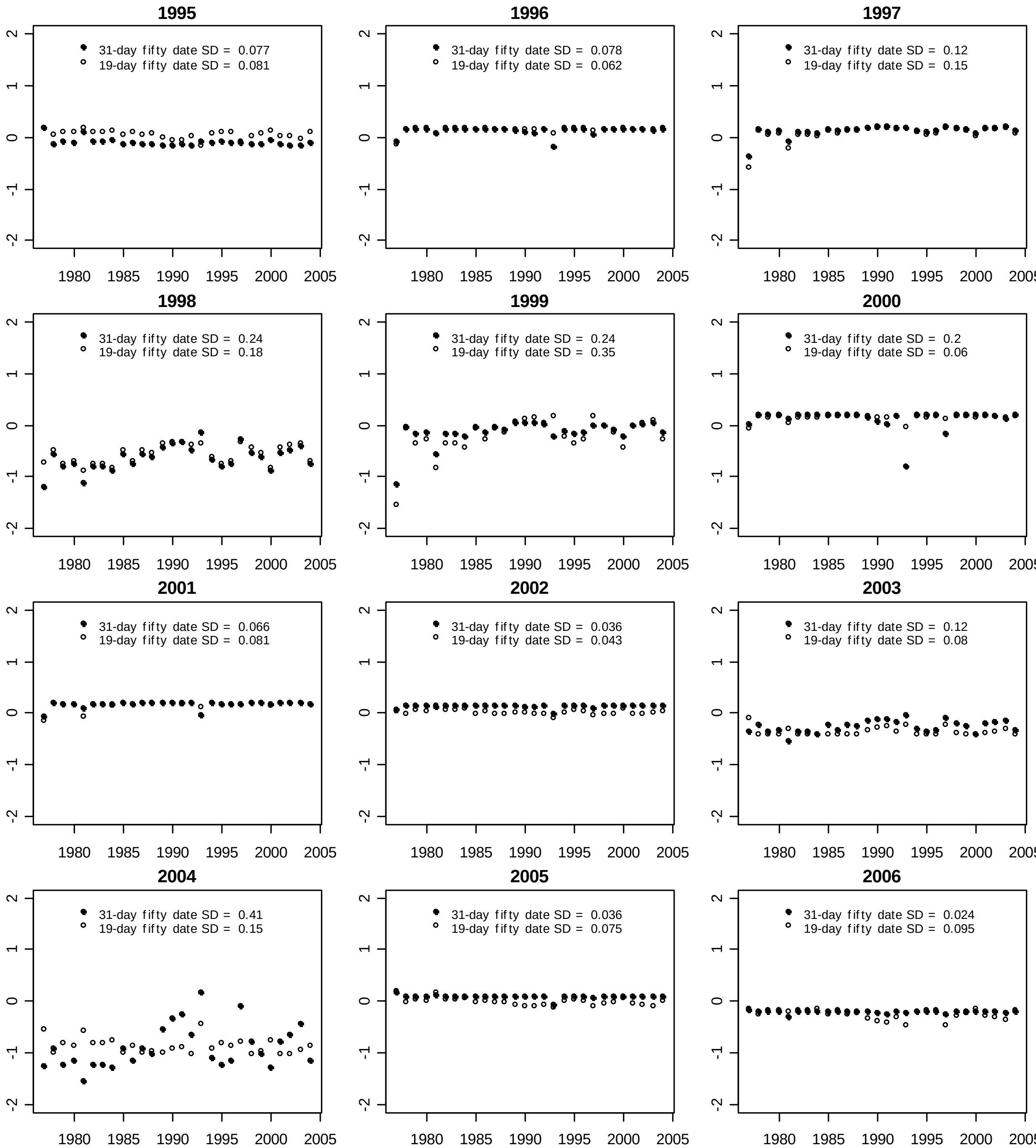

Figure 7. Sensitivity (SD) of Summer 19-day asymmetric and 31-day symmetric MA model predictions (y-axis) to changes in 50% date (open points = 19-day asymmetric; closed points = 31-day symmetric) under different years of observed Fraser River temperature and discharge conditions (x-axis). Timing and profile variability was represented by historic values from 1977 - 2004.

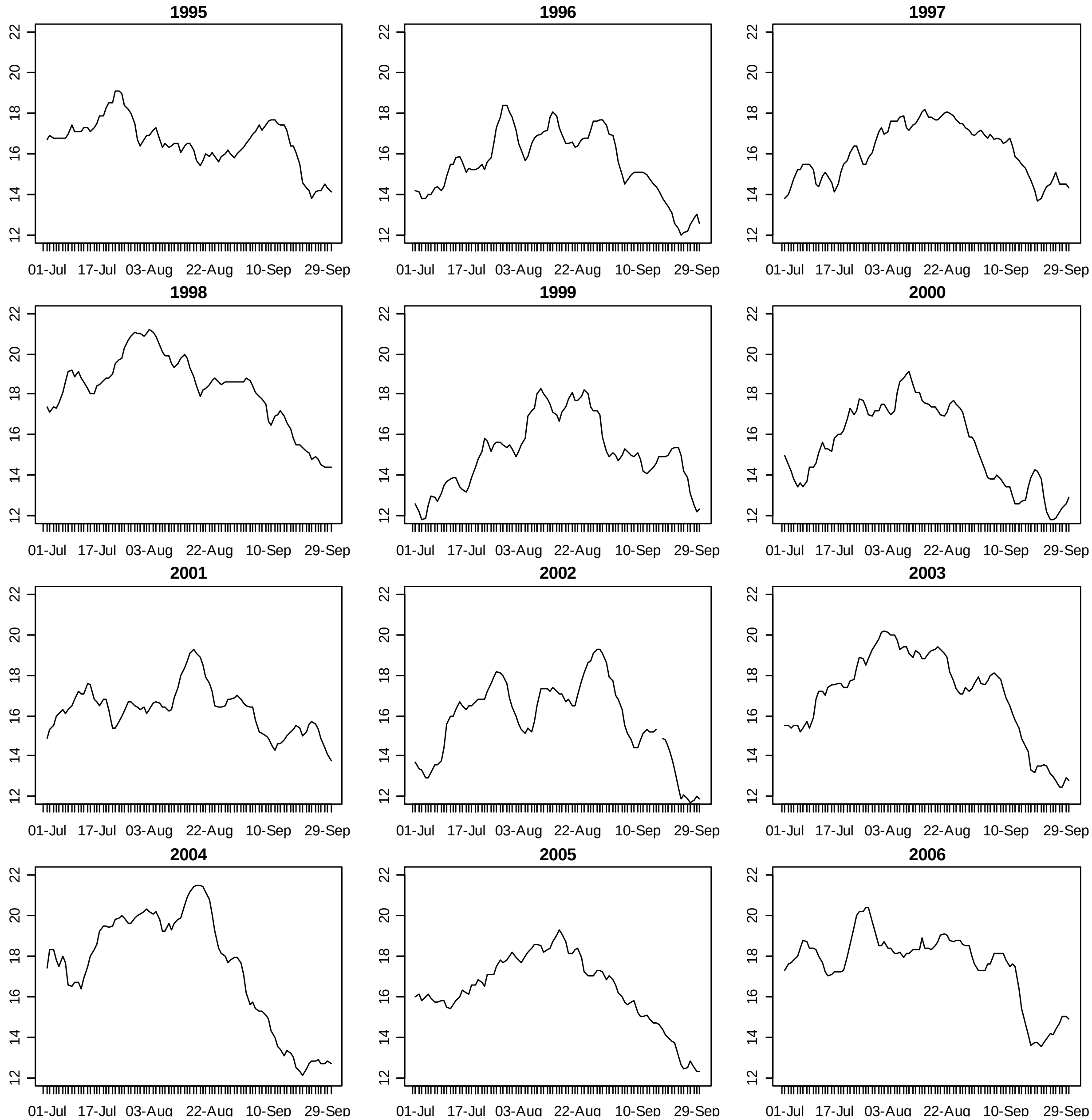

Figure 8. Daily Fraser River water temperature (^{o}C) conditions at Qualark for the same years as used to create the MA forecasts in Figures 1 to 3. Y-axis is temperature (^{o}C) and x-axis is date.

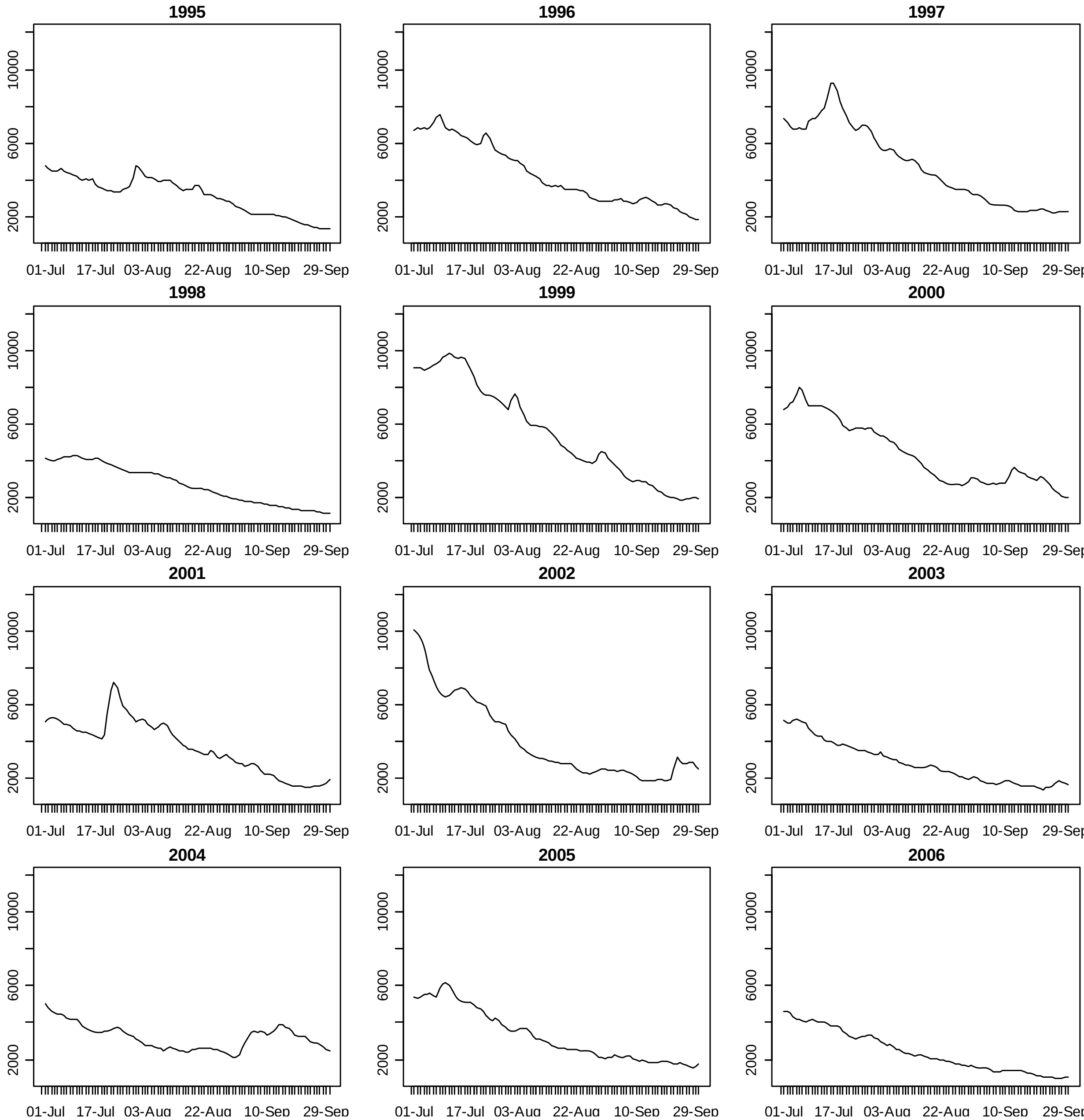

Figure 9. Daily Fraser River water discharge (cms) conditions at Hope for the same years as used to create the MA forecasts in Figures 1 to 3. Y-axis is temperature (^{o}C) and x-axis is date.

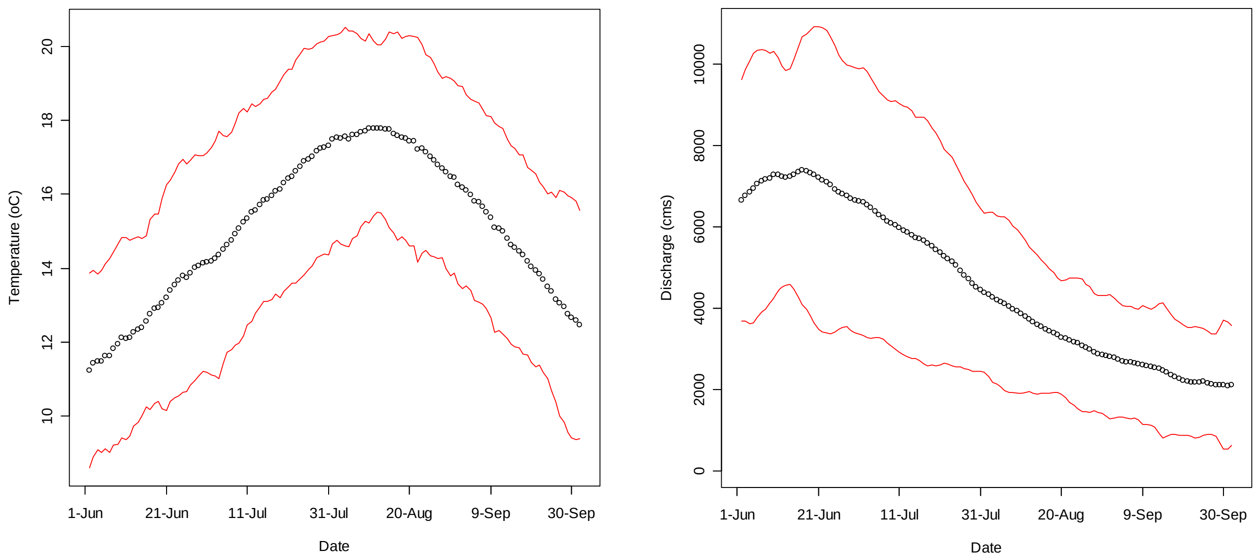

Figure 10. Points show average historic (1950 – 2005) thermograph (left) and hydrograph (right) for summer Fraser River temperature and discharge conditions. Solid lines are +/- 2 SDs.

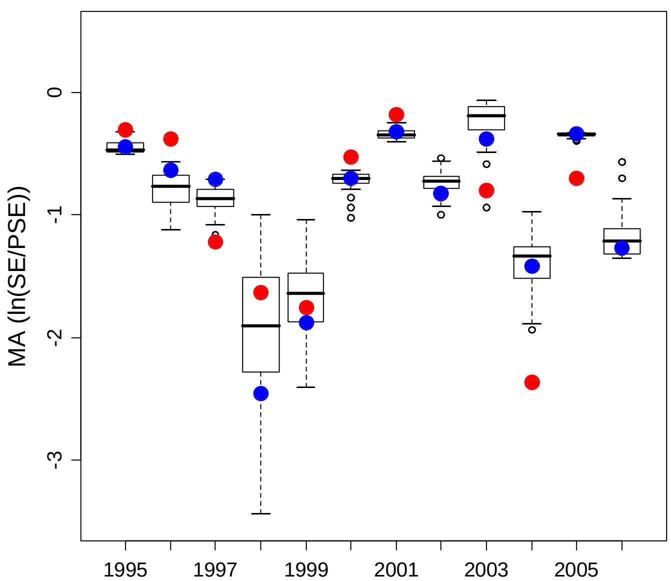

Figure 11. Early Stuart MA retrospective 50% date uncertainty analysis. Run timing error structure was simulated using the Early Stuart oceanographic 50% date forecasting model. Boxes capture the 25th to 75th quartiles. The solid lines in the boxes illustrate the median MA. Error bars = 1.5*interquartile range. Open black points are outliers outside of the range of the error bars. Solid red points indicate the observed Early Stuart MA for each year. Solid blue points indicate the forecasted MA assuming no error in the oceanographic run timing model (i.e. using mean forecasted 50% date). Models use observed 31-day symmetric mean river temperature and discharge data and assume no MA model error.

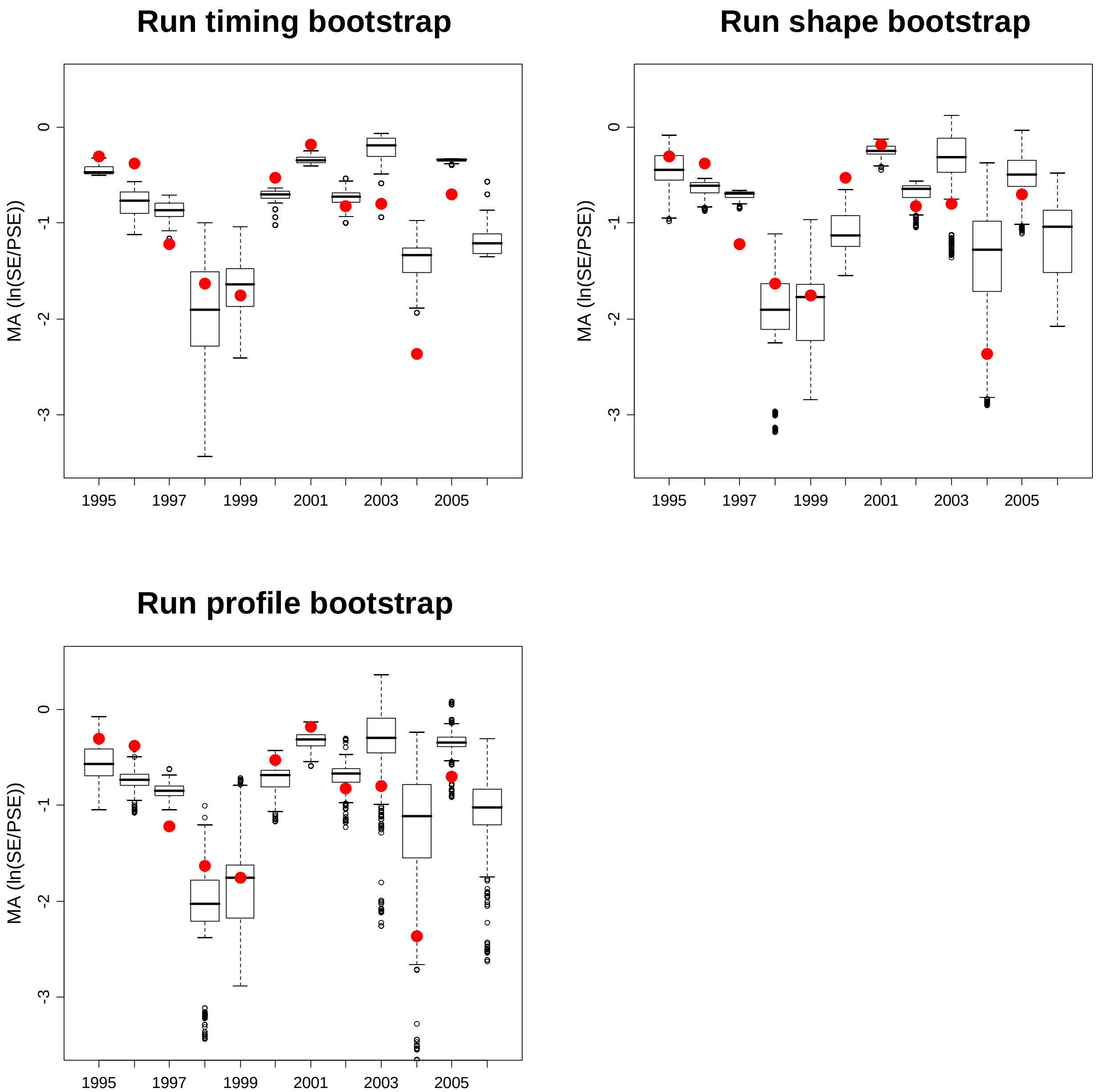

Figure 12. Early Stuart MA retrospective 50% date (upper left), run shape (upper right) and run profile (lower left; combined changes in run timing and run shape) uncertainty analysis. Error structures were simulated using a non-parametric bootstrap of historic 50% dates and run profile shapes. Boxes capture the 25th to 75th quartiles. The solid lines in the boxes illustrate the median MA. Error bars = 1.5*interquartile range. Open points are outliers outside of the range of the error bars. Large solid points indicate the observed Early Stuart MA for each year. Models use observed 31-day average (50% date model) or run profile weighted average (run shape and run profile models) river temperature and discharge data and assume no MA model error.

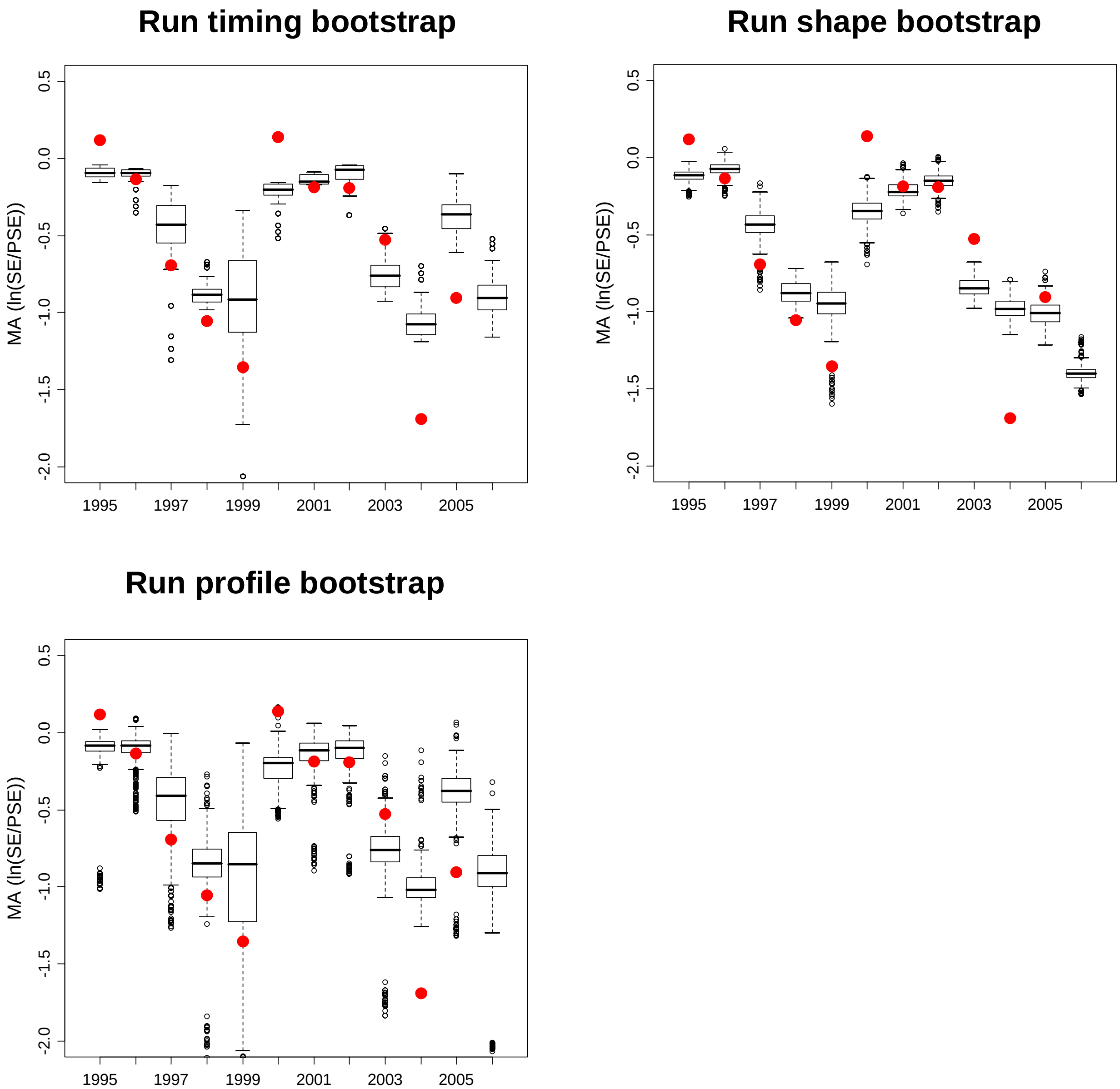

Figure 13. Early Summer MA retrospective 50% date (upper left), run shape (upper right) and run profile (lower left; combined changes in run timing and run shape) uncertainty analysis. Error structure was simulated using a non-parametric bootstrap of historic 50% dates and run profile shapes. Boxes capture the 25th to 75th quartiles. The solid lines in the boxes illustrate the median MA. Error bars = 1.5*interquartile range. Open points are outliers outside of the range of the error bars. Large solid points indicate the observed Early Summer MA for each year. Models use observed 31-day average (50% date model) or run profile weighted average (run shape and run profile models) river temperature and discharge data and assume no MA model error.

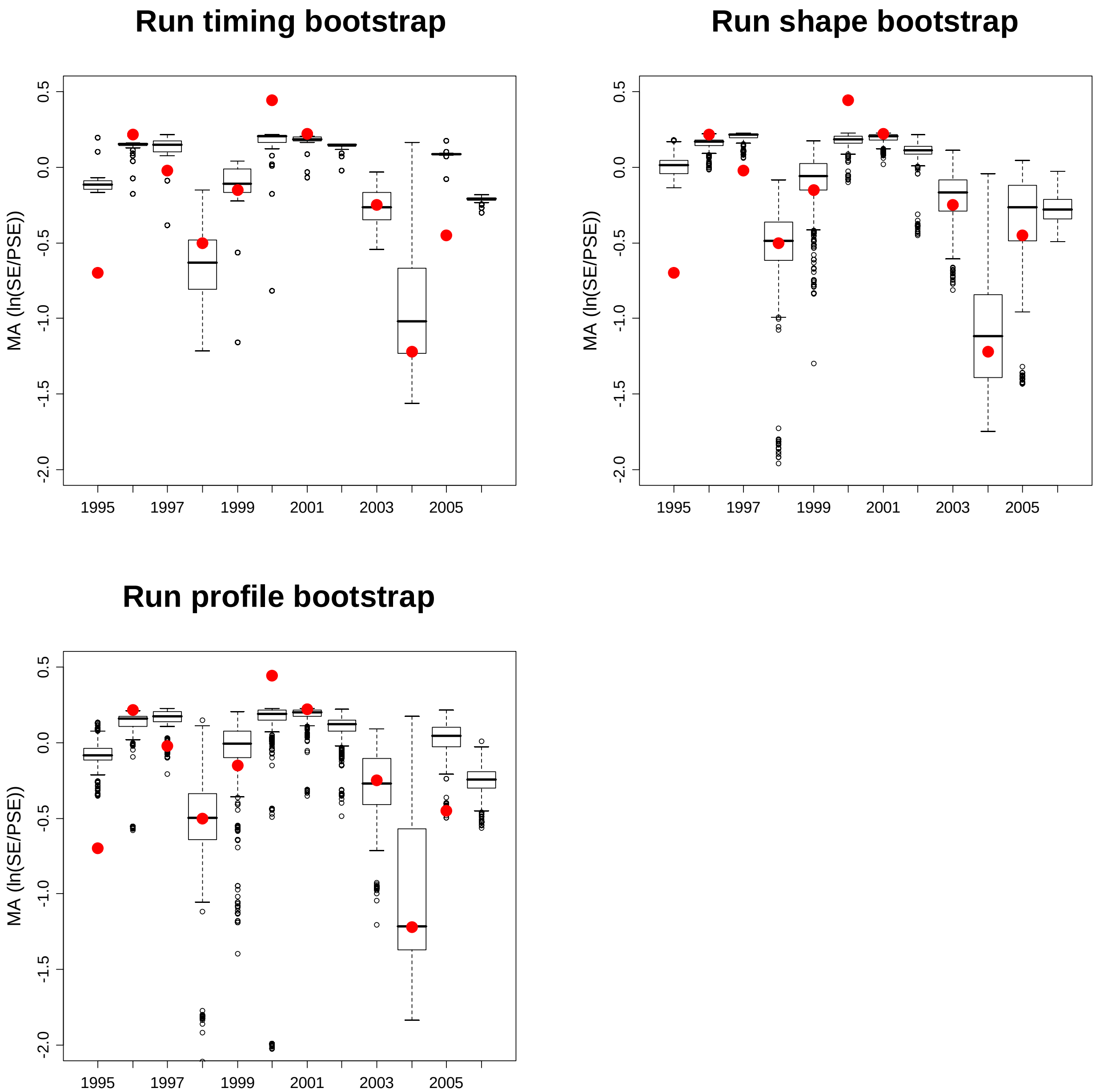

Figure 14. Summer MA retrospective 50% date (upper left), run shape (upper right), and run profile (lower left; changes to both run timing and run shape) uncertainty analysis. Error structure was simulated using a non-parametric bootstrap of historic 50% dates and run shapes. Boxes capture the 25th to 75th quartiles. The solid lines in the boxes illustrate the median MA. Error bars = 1.5*interquartile range. Open points are outliers outside of the range of the error bars. Large solid points indicate the observed Summer MA for each year. Models use observed 31-day average (50% date model) or run profile weighted average (run shape and run profile models) river temperature and discharge data and assume no MA model error.

ACKNOWLEDGEMENTS

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EXECUTIVE SUMMARY

- **Purpose:** Determine whether Fraser River sockeye salmon MA models should be modified to better represent uncertainties in timing and shape of run distributions
- **Objectives:**
  - evaluate Mission run timing profiles to determine if the biological rationale behind the MA model is met
  - test sensitivity of MA models to changes in run timing, run shape and run profile (combined changes in timing and shape)
  - examine effect of including run timing, run shape or run profile uncertainty on MA predictions
- Biological rationale behind pre-season MA models assumes:
  - 31-day mean around 50% date captures the majority of the run profile
  - run profiles are equally distributed on either side of the 50% date
  - an un-weighted mean adequately represents environmental conditions experienced by the salmon
- **Results summary:**
  - mixed normal distribution provided best-fit to most historic profiles
  - 31-day period capture >90% of most run distributions
  - Daily run proportion weighted MA models had a lower r^2 than the 31-day symmetric models for all groups, but a higher r^2 than 19-day asymmetric models
  - weighted MA models still provided good fits to Summer and Late-run data
  - Early Stuart MA model most sensitive to changes in run timing, run shape and run profile
  - MA sensitivity to run timing, run shape and run profile varied across years (generally more sensitive during high temperature and discharge years)
  - models incorporating run timing or run shape uncertainty alone predicted historic MAs better, on average, than models which incorporated both run timing and run shape uncertainty (i.e. run profile uncertainty)
  - Early Summer and Summer run shape uncertainty models produced slightly better average MA predictions than run timing uncertainty models
- **Recommendations:**
  - continue with use of 31-day symmetric mean pre-season models
  - consider alternative 50% date and environmental forecasting models in-season to facilitate switch from a 19-day asymmetric to 31-day symmetric in-season model
  - archive river temperature records later into the fall for better evaluation of Late-run models
  - incorporate uncertainty in 50% date into models; continue to evaluate the benefits of including this uncertainty
  - present MA forecasts for a range of dates for each run group
  - develop and evaluate cumulative exposure models as they may better represent the true environmental conditions experienced by each run

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APPENDIX A: HISTORIC RUN PROFILES

Table A1. Summary statistics for testing of the basic assumptions of the current management adjustment model with respect to run profile distributions for the Early Stuart run.

Year	Days before - days after 50% date	Skewness test results	Kurtosis test results	Bi-modal (Y/N)	Total run length (days)	Mission estimate	% of run captured by 31-day mean	% of run captured by 19-day mean
1977	2	1.3	0.5	m	31	344 694	100[1]	87
1978	-4	0.5	0.0	N	23	140 700	100[2]	78[2]
1979	-11	1.2	0.0	N	34	211 499	91[2]	79[2]
1980	-6	0.6	-0.2	N	21	43 700	100[1,2]	66[2]
1981	-4	1.5	0.7	N	39	334 600	98	78
1982	-8	2.0	5.3	N	35	89 500	98[2]	65[2]
1983	-8	2.1	5.1	N	29	105 500	99[2]	68[2]
1984	-4	1.2	0.8	N	27	50 714	100[2]	63[2]
1985	1	0.3	-0.5	Y	34	294 916	98	62[2]
1986	-12	0.2	-1.4	Y	33	38 514	96[2]	69
1987	-2	0.9	0.4	N	35	174 803	99	70[2]
1988	-6	0.9	-0.3	N	35	192 191	98[2]	74
1989	-7	1.2	0.5	Y	38	464 618	93	66
1990	-6	1.2	0.4	N	37	167 389	97	72
1991	2	0.4	-1.1	N	39	369 412	98	66
1992	-7	0.8	-0.4	N	44	324 098	95	68
1993	-1	1.2	0.4	N	44	701 973	98	80
1994	1	1.4	1.6	N	36	193 559	99	76
1995	3	1.0	-0.4	N	28	171 517	100[1]	77
1996	7	1.4	1.5	N	30	130 626	99[1]	75
1997	12	0.8	-0.3	N	41	1 259 456	96[1]	68
1998	3	0.7	-0.7	N	32	183 679	100[1]	78
1999	-8	1.8	3.2	N	25	166 910	100[2]	67[2]
2000	3	0.2	-1.3	N	32	340 278	100[1]	66
2001	-2	0.7	-0.7	N	45	240 557	95	63
2002	1	1.0	0.3	m	28	61 311	100[1,2]	63[2]
2003	-5	1.3	0.5	N	30	29 486	98[1]	79[2]
2004	4	0.3	-1.3	m	35	128 919	98	62
2005	15	1.1	-0.4	N	40	216 745	94[1]	73
2006	1	0.9	0.4	N	40	67 558	66	66

Notes: [1] Includes days after the run has passed Mission.
[2] Includes days before the run has passed Mission.
m = small multiple modes (often smoothed out if a moving average is applied)

Table A2. Summary statistics for testing of the basic assumptions of the current management adjustment model with respect to run profile distributions for the Early Summer run.

Year	**Days before - days after 50% date**	**Skewness test results**	**Kurtosis test results**	**Bi-modal (Y/N)**	**Total run length (days)**	**Mission estimate**	**% of run captured by 31-day mean**	**% of run captured by 19-day mean**
1977	6	3.0	8.4	N	37	76 508	96	90
1978	10	1.9	4.9	m	59	92 000	75	54
1979	0	2.1	3.7	m	47	282 225	98	76
1980	16	1.6	1.5	N	35	102 300	97[1]	83
1981	10	1.4	0.6	Y	41	86 050	94	75
1982	14	3.5	15.6	m	53	145 100	78	60
1983	2	1.3	0.8	Y	57	214 700	86	53
1984	-2	2.6	8.1	N	39	122 186	95	62
1985	3	2.3	5.5	m	66	55 368	85	50
1986	6	2.4	5.2	N	65	232 852	93	74
1987	3	1.8	2.9	m	58	425 097	88	63
1988	14	2.0	3.7	N	43	489 558	92[1]	76
1989	18	2.0	3.8	N	39	113 910	94[1]	73
1990	19	4.5	23.9	m	58	682 846	91	69
1991	-4	1.2	0.2	m	57	516 762	76	51
1992	1	2.0	4.4	N	50	369 794	94	70
1993	9	1.3	0.3	N	42	25 260	98	67
1994	11	1.7	2.7	Y	52	470 687	87	50
1995	16	0.7	-0.7	N	49	197 636	96	62
1996	13	1.3	1.5	Y	48	441 143	92	63
1997	18	1.2	0.5	m	45	137 209	95[1]	58
1998	18	2.1	4.2	m	45	472 108	97[1]	64
1999	12	0.8	-0.6	N	51	323 605	94	68
2000	5	1.0	-0.4	Y	52	618 867	95	54
2001	11	0.6	0.3	m	52	261 967	75	51
2002	12	1.1	-0.2	N	49	506 881	97	66
2003	8	1.8	3.0	m	53	240 207	87	63
2004	-23	1.2	0.7	N	82	637 661	84	57
2005	40	2.6	8.0	Y	85	457 249	73	45
2006	10	1.4	1.7	N	75	699 073	84	61

Notes: [1] Includes days after the run has passed Mission.
[2] Includes days before the run has passed Mission.
m = small multiple modes (often smoothed out if a moving average is applied)

Table A3. Summary statistics for testing of the basic assumptions of the current management adjustment model with respect to run profile distributions for the Summer run.

Year	Days before - days after 50% date	Skewness test results	Kurtosis test results	Bi-modal (Y/N)	Total run length (days)	Mission estimate	% of run captured by 31-day mean	% of run captured by 19-day mean
1977	-12	3.2	9.4	N	47	773 398	97	79
1978	0	1.9	3.6	Y	55	337 200	94	49
1979	-23	2.9	8.4	m	56	715 379	94	74
1980	3	1.4	0.6	m	40	743 600	97	83
1981	-7	2.1	3.1	Y	60	1 458 900	97	62
1982	5	2.3	5.8	N	48	520 200	85	60
1983	-1	0.9	-0.1	N	42	572 700	97	73
1984	-18	3.6	15.4	m	79	1 081 007	77	67
1985	-8	3.6	14.6	N	85	1 933 697	89	74
1986	-6	1.1	-0.3	Y	53	1 021 653	97	62
1987	1	2.2	5.8	m	62	640 521	95	55
1988	-13	2.5	6.4	Y	60	637 848	96	83
1989	-2	2.7	7.3	m	61	2 882 933	81	70
1990	2	2.2	5.5	m	73	2 293 367	86	52
1991	2	1.8	3.1	m	57	1 414 415	80	45
1992	9	1.4	1.7	m	54	1 080 239	95	62
1993	8	1.7	3.2	Y	77	4 341 731	82	57
1994	-9	2.0	3.8	Y	66	2 355 670	90	70
1995	-17	1.8	2.8	N	70	1 452 329	88	66
1996	1	1.9	3.4	N	52	1 564 626	96	73
1997	-10	2.9	9.0	N	75	4 244 736	80	67
1998	-7	1.3	0.8	m	60	4 372 540	87	55
1999	-5	0.4	-1.3	N	70	1 631 029	82	50
2000	2	1.3	0.8	N	53	1 335 329	92	55
2001	-2	0.8	-0.8	N	67	4 170 794	84	53
2002	5	0.8	-0.6	N	74	4 654 169	86	56
2003	9	1.0	-0.3	Y	80	1 637 971	83	49
2004	-8	1.3	0.9	N	77	1 210 754	91	65
2005	20	1.8	2.3	Y	63	4 339 689	87	58
2006	-15	1.5	2.5	N	68	833 814	85	59

Notes: m = small multiple modes (often smoothed out if a moving average is applied)

Table A4. Summary statistics for testing of the basic assumptions of the current management adjustment model with respect to run profile distributions for the Late run.

Year	**Days before - days after 50% date**	**Skewness test results**	**Kurtosis test results**	**Bi-modal (Y/N)**	**Total run length (days)**	**Mission estimate**	**% of run captured by 31-day mean**	**% of run captured by 19-day mean**
1977	18	1.6	4.6	m	47	114 000	80[1]	45
1978	6	1.8	2.1	N	45	1 888 700	99	76
1979	16	1.6	3.2	N	41	543 240	95[1]	59
1980	32	1.5	1.3	N	51	159 300	95[1]	61
1981	16	0.9	-0.4	N	41	92 599	86[1]	46
1982	16	1.4	0.1	N	45	3 533 100	100[1]	82
1983	8	1.3	1.1	Y	41	412 500	97	58
1984	14	2.1	4.0	N	33	60 540	94[1]	71
1985	21	1.8	2.4	N	36	73 309	88[1]	68
1986	-5	2.5	5.5	N	38	3 499 388	98	91
1987	18	1.4	1.4	m	55	647 652	94	61
1988	5	1.0	-0.3	m	32	192 952	89[1]	52
1989	10	0.7	-0.4	N	31	140 452	100[1]	58
1990	8	1.1	0.1	N	49	3 158 883	94	65
1991	-4	2.6	6.8	N	47	1 532 806	94	72
1992	0	1.2	1.0	m	33	87 611	95	59
1993	9	1.0	0.1	m	30	85 688	98	67
1994	35	2.6	6.7	N	74	975 297	87	57
1995	12	1.7	1.8	Y	47	498 213	89	44
1996	12	1.7	2.7	N	45	450 637	95	69
1997	-8	1.1	1.0	m	37	79 448	98[2]	60[2]
1998	23	2.3	4.4	N	34	2 983 862	91[1]	89
1999	6	1.6	2.9	N	49	968 333	82	42
2000	-6	1.1	1.0	m	35	356 443	89[2]	68[2]
2001	-7	1.0	0.4	m	50	309 829	84	54
2002	56	2.4	6.0	Y	79	6 509 132	81[1]	55
2003	3	2.3	6.5	Y	54	693 319	68	45
2004	0	1.3	1.2	N	63	189 856	84	56
2005	12	3.4	14.4	Y	63	406 780	64	40
2006	27	1.4	1.4	N	68	2 036 742	78	50

Notes: [1] Includes days after the run has passed Mission.
[2] Includes days before the run has passed Mission.
m = small multiple modes (often smoothed out if a moving average is applied)

APPENDIX B: RUN DISTRIBUTION MODEL FITTING

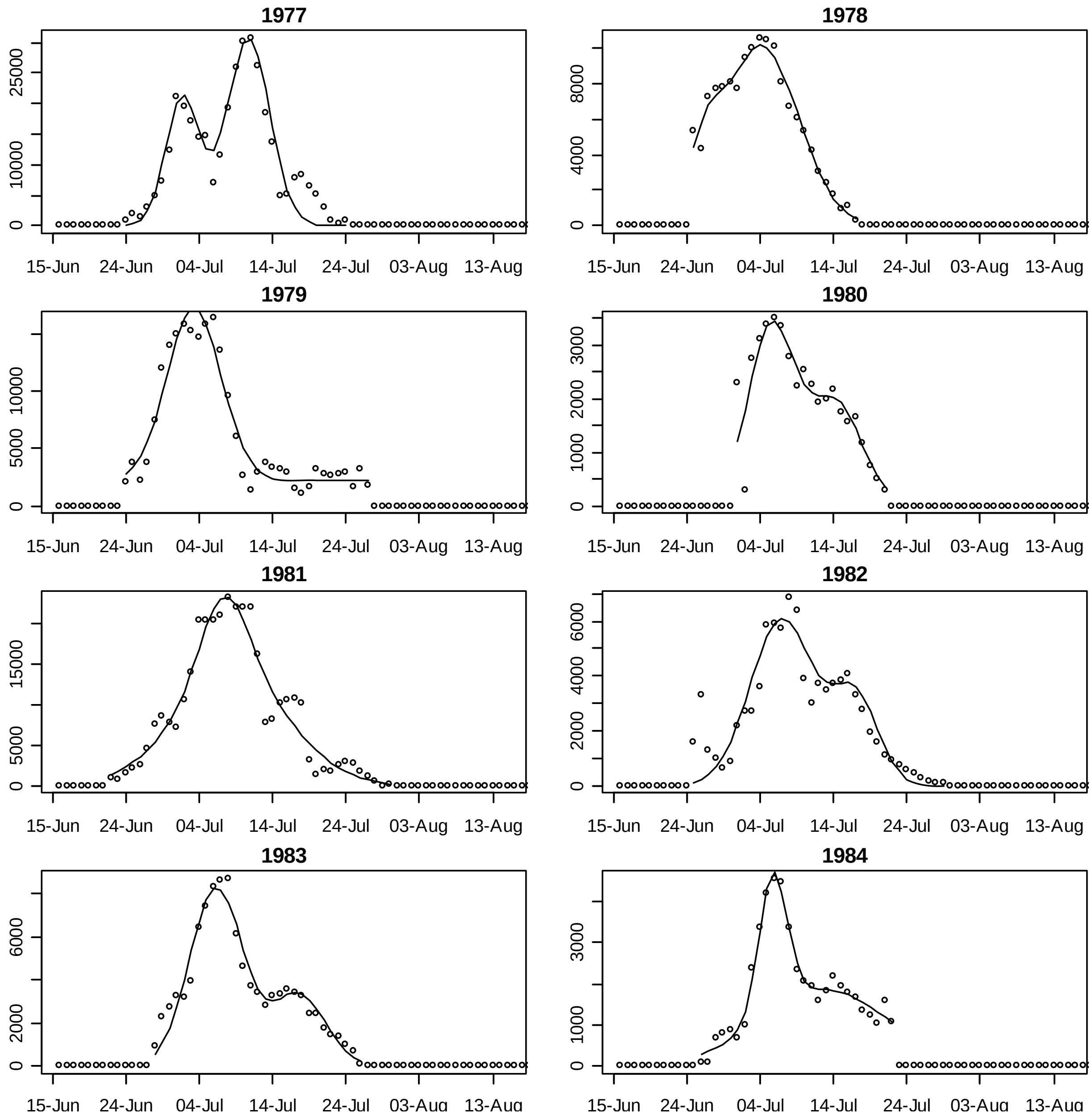

Figure B1a. Early Stuart run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1986 (gamma), 1995 (normal) and 2001 (normal).

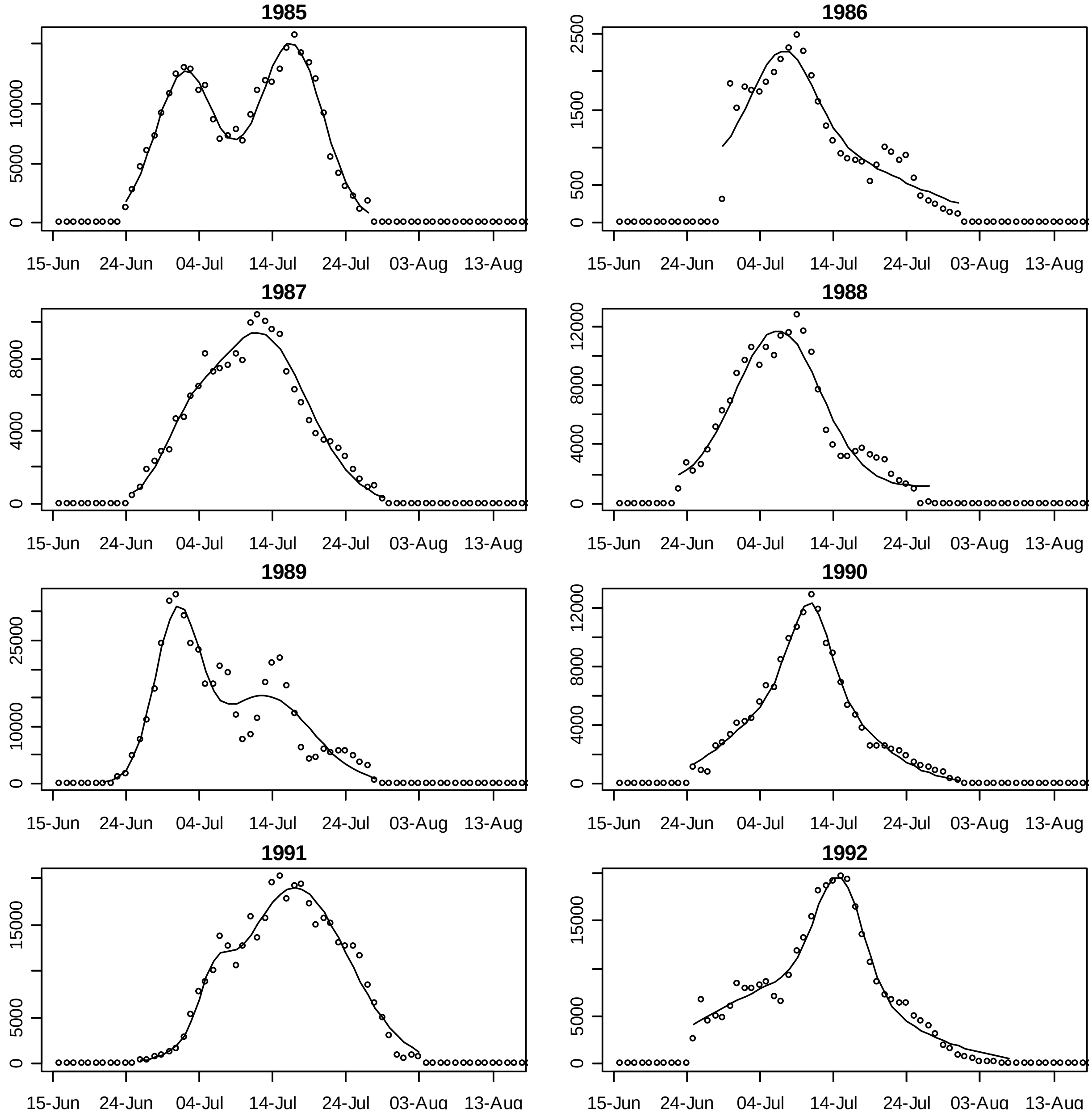

Figure B1b. Early Stuart run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1986 (gamma), 1995 (normal) and 2001 (normal).

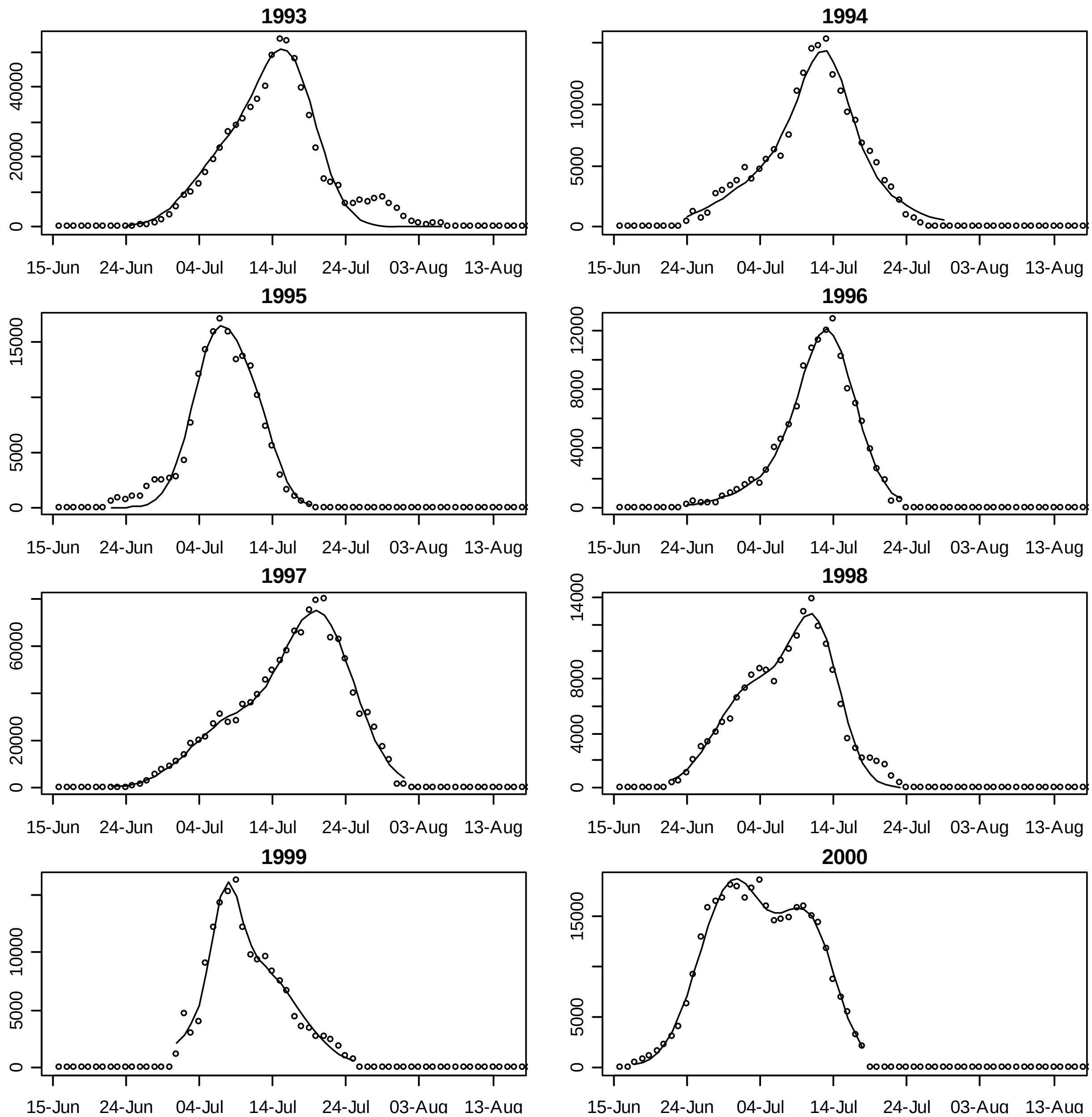

Figure B1c. Early Stuart run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1986 (gamma), 1995 (normal) and 2001 (normal).

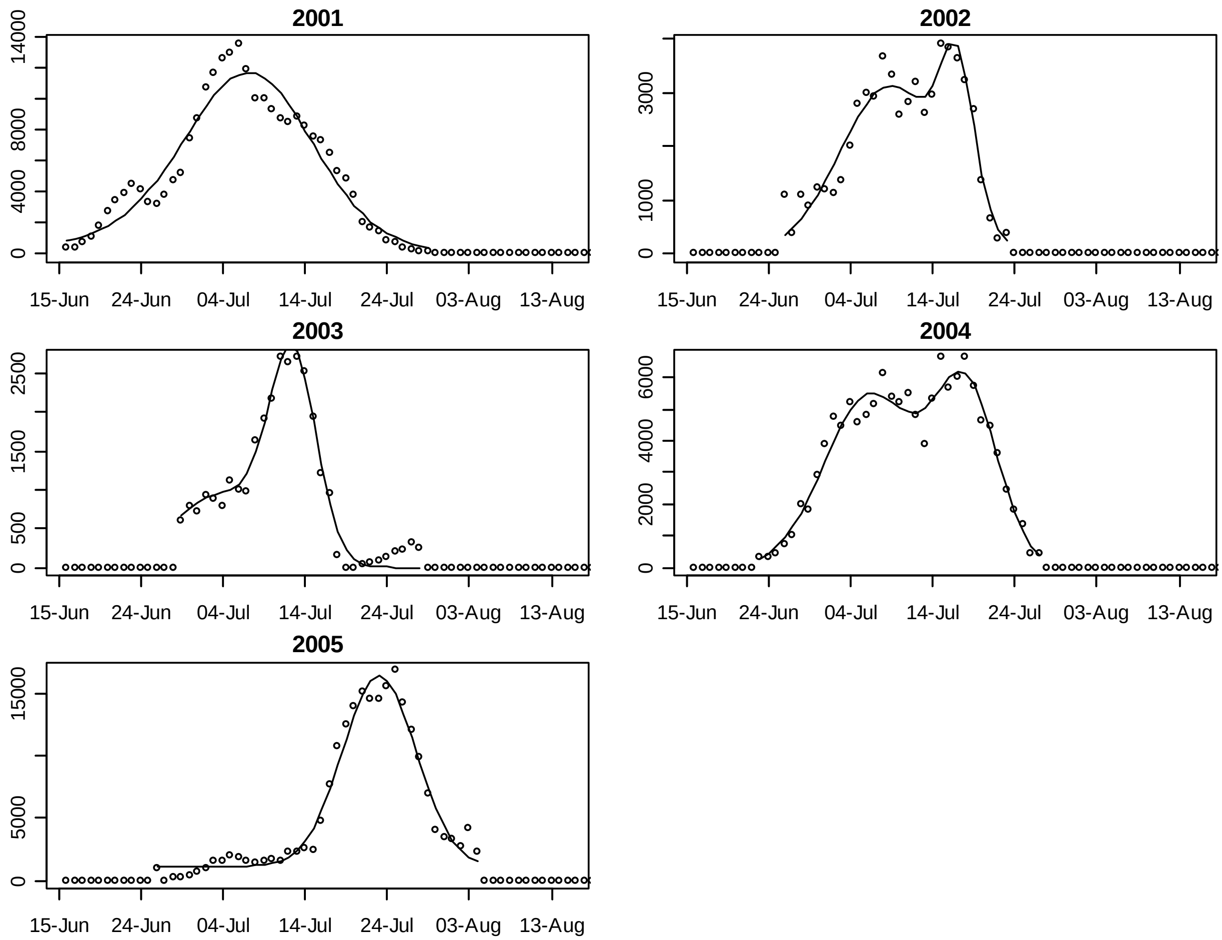

Figure B1d. Early Stuart run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1986 (gamma), 1995 (normal) and 2001 (normal).

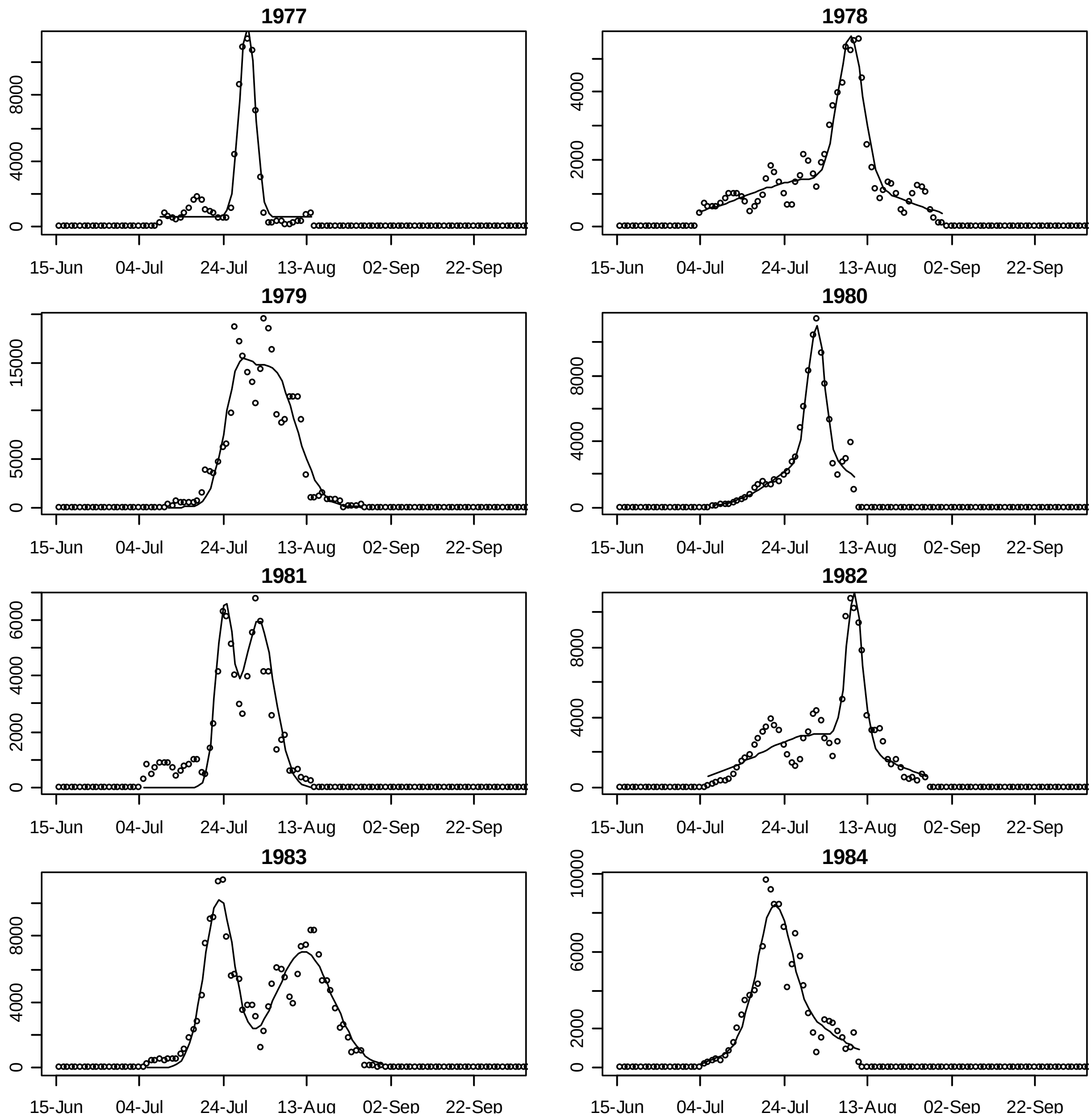

Figure B2a. Early Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1985 (normal), 2001 (gamma) and 2004 (normal).

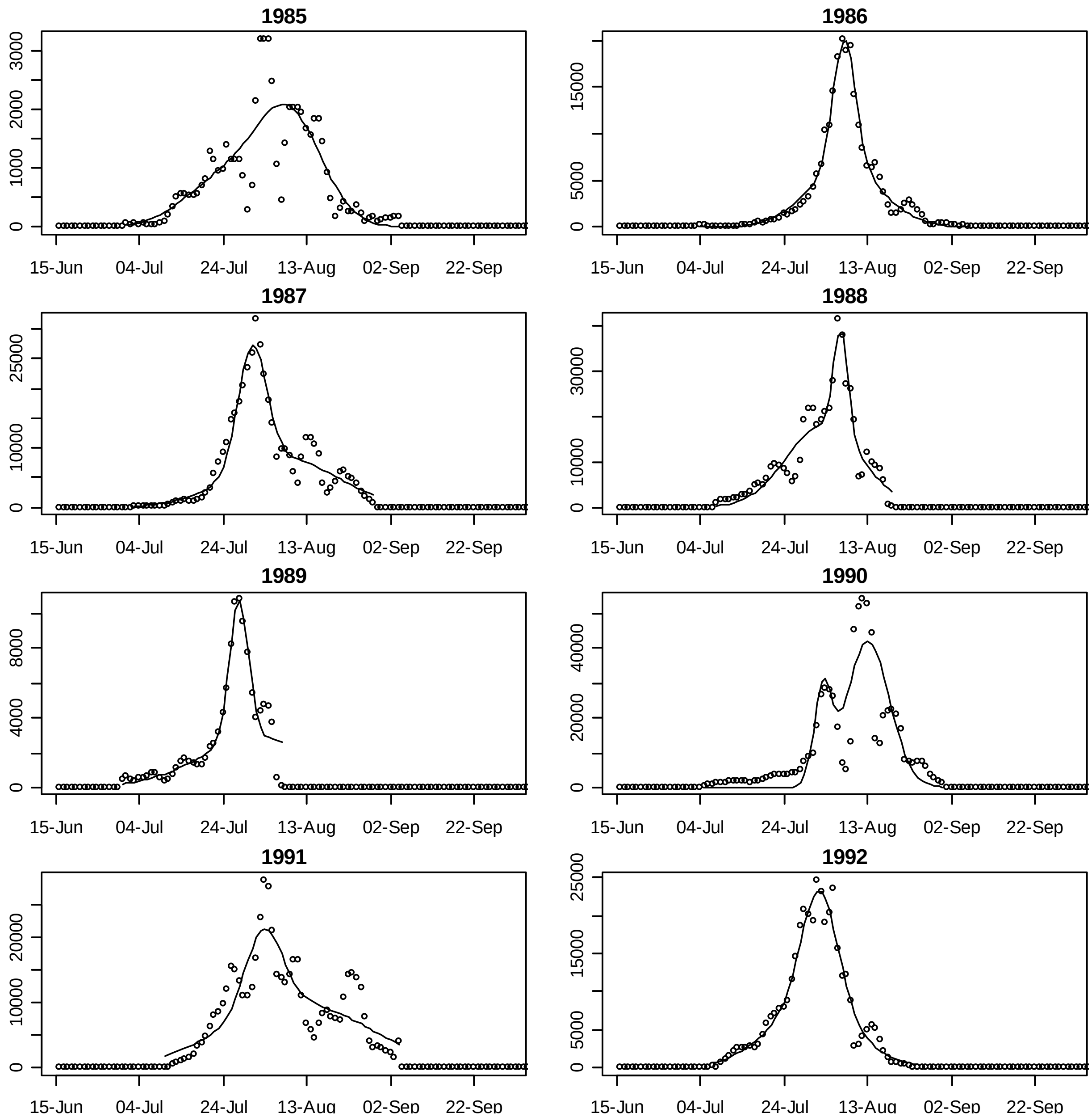

Figure B2b. Early Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1985 (normal), 2001 (gamma) and 2004 (normal).

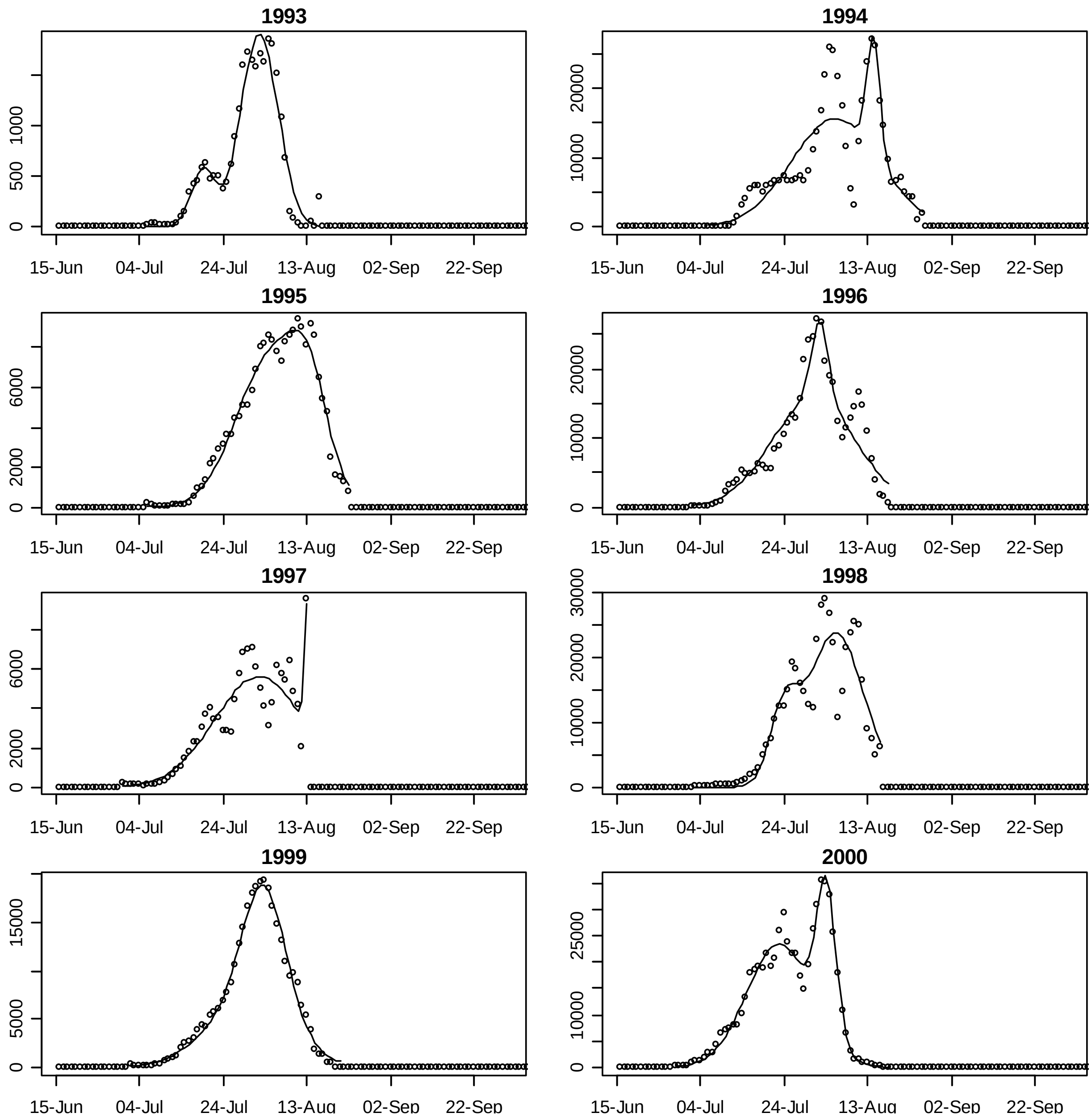

Figure B2c. Early Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1985 (normal), 2001 (gamma) and 2004 (normal).

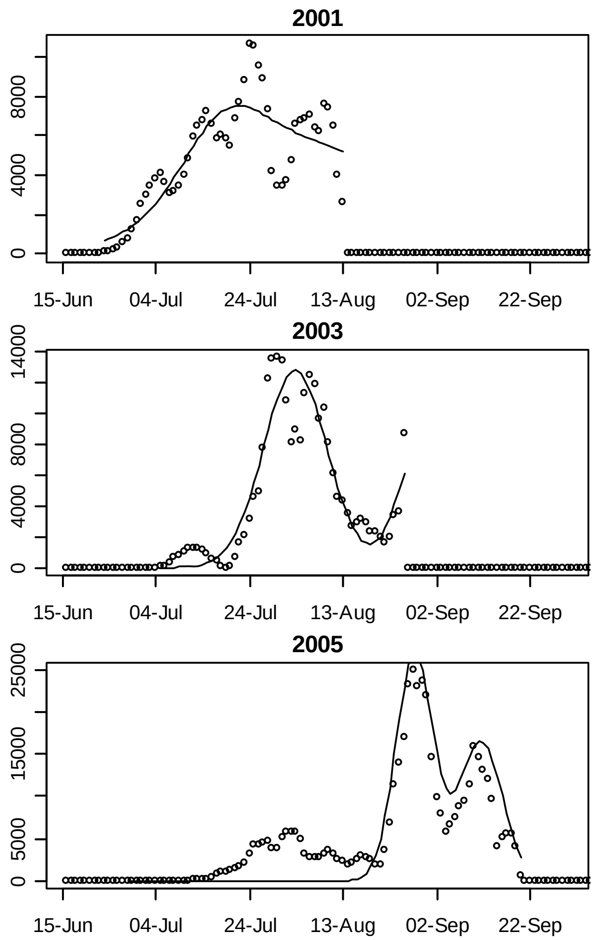

Figure B2d. Early Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1985 (normal), 2001 (gamma) and 2004 (normal).

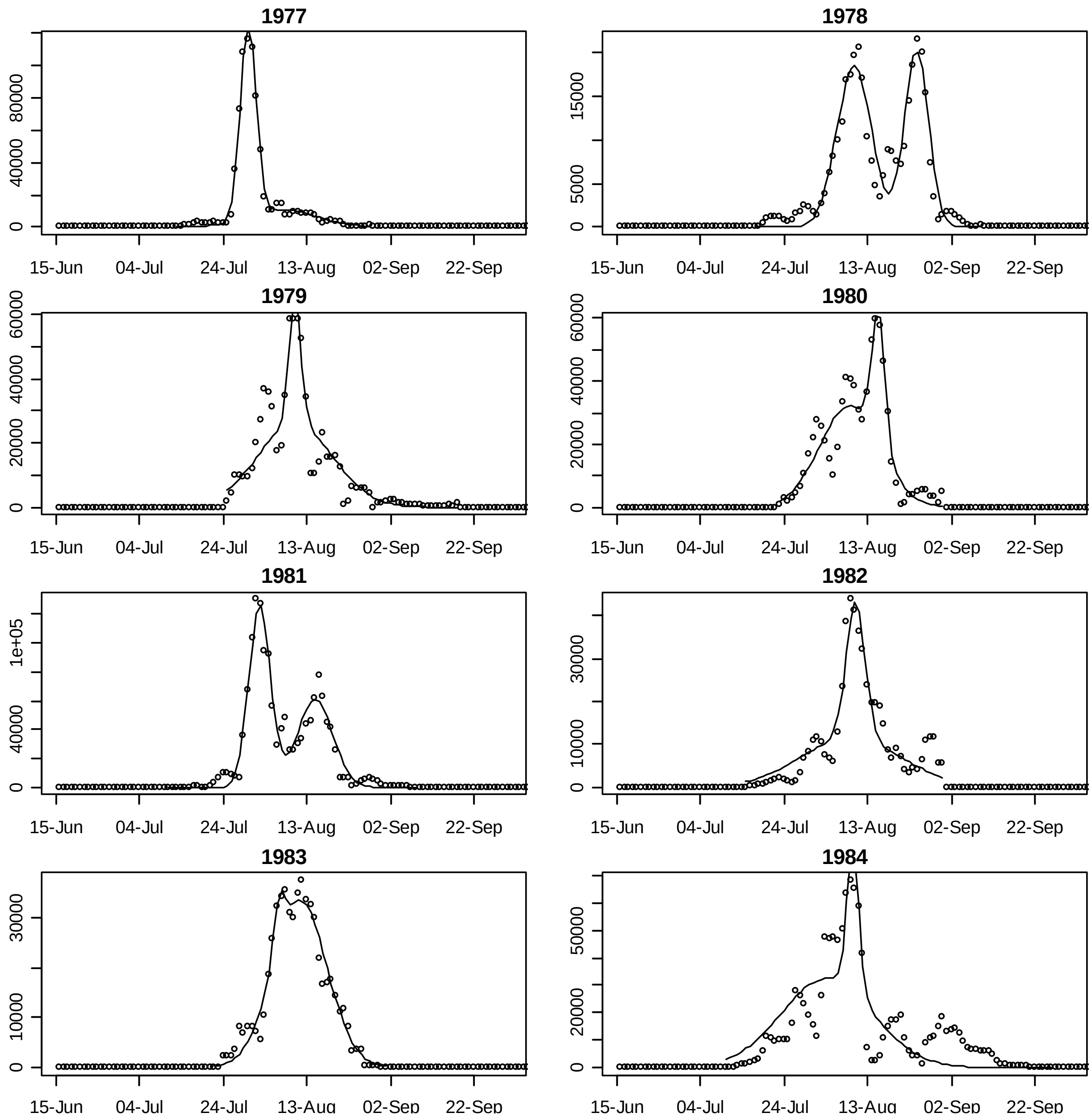

Figure B3a. Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years.

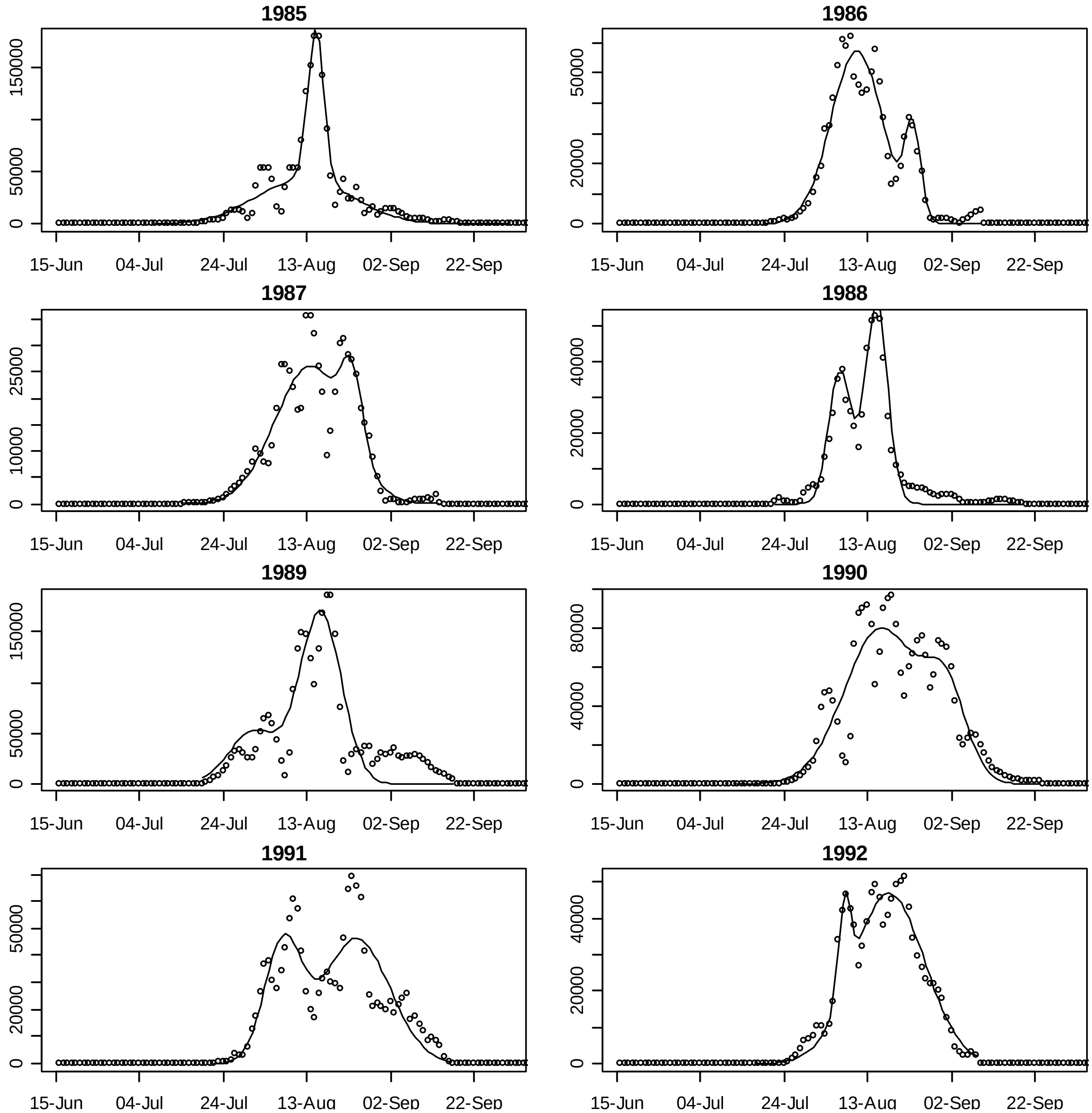

Figure B3b. Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years.

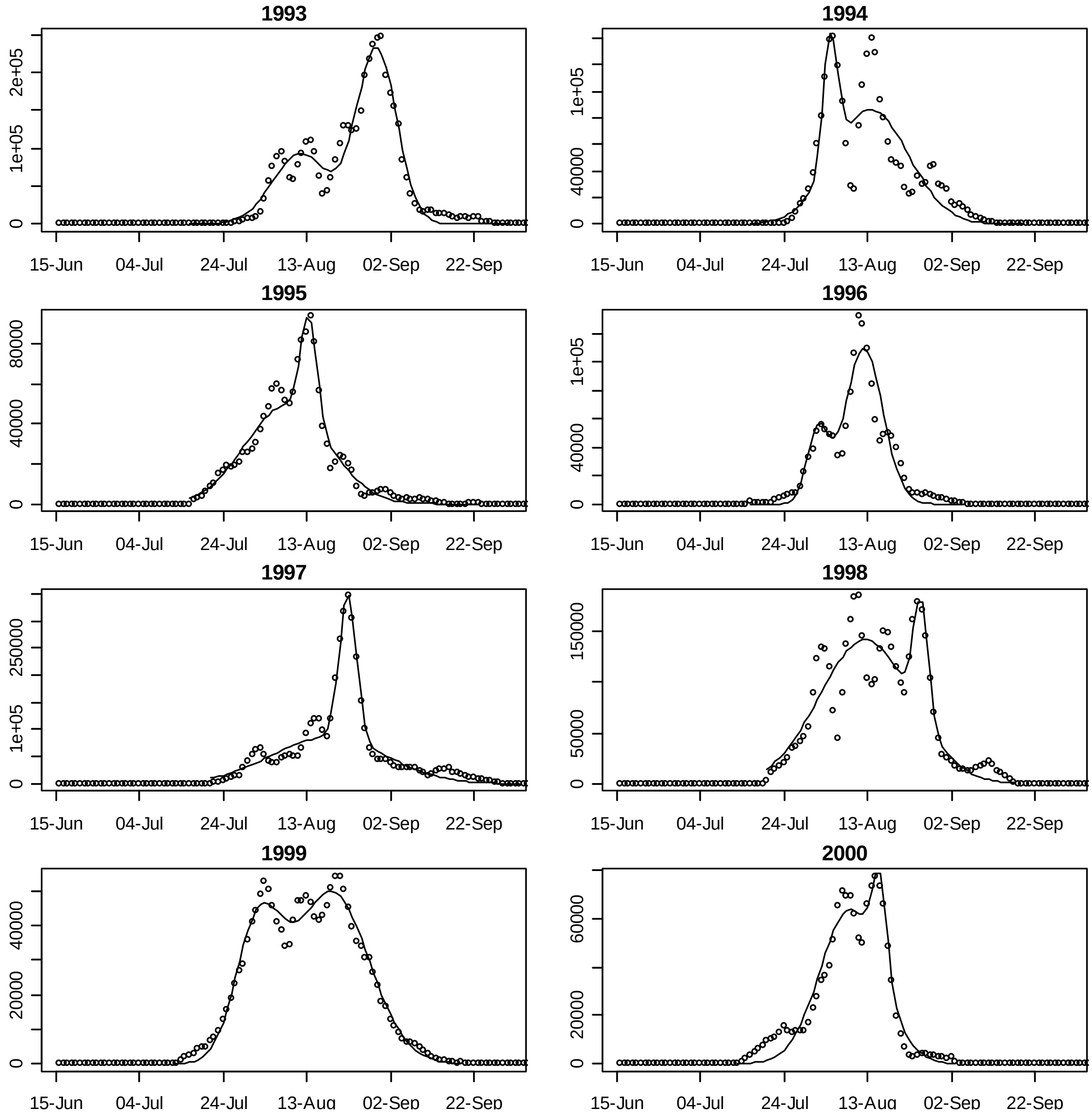

Figure B3c. Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years.

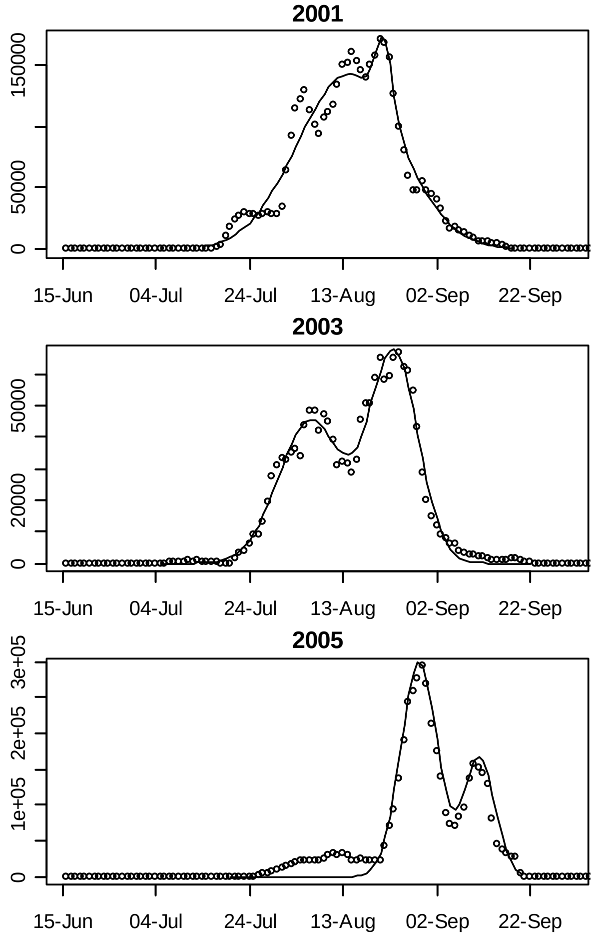

Figure B3d. Summer run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years.

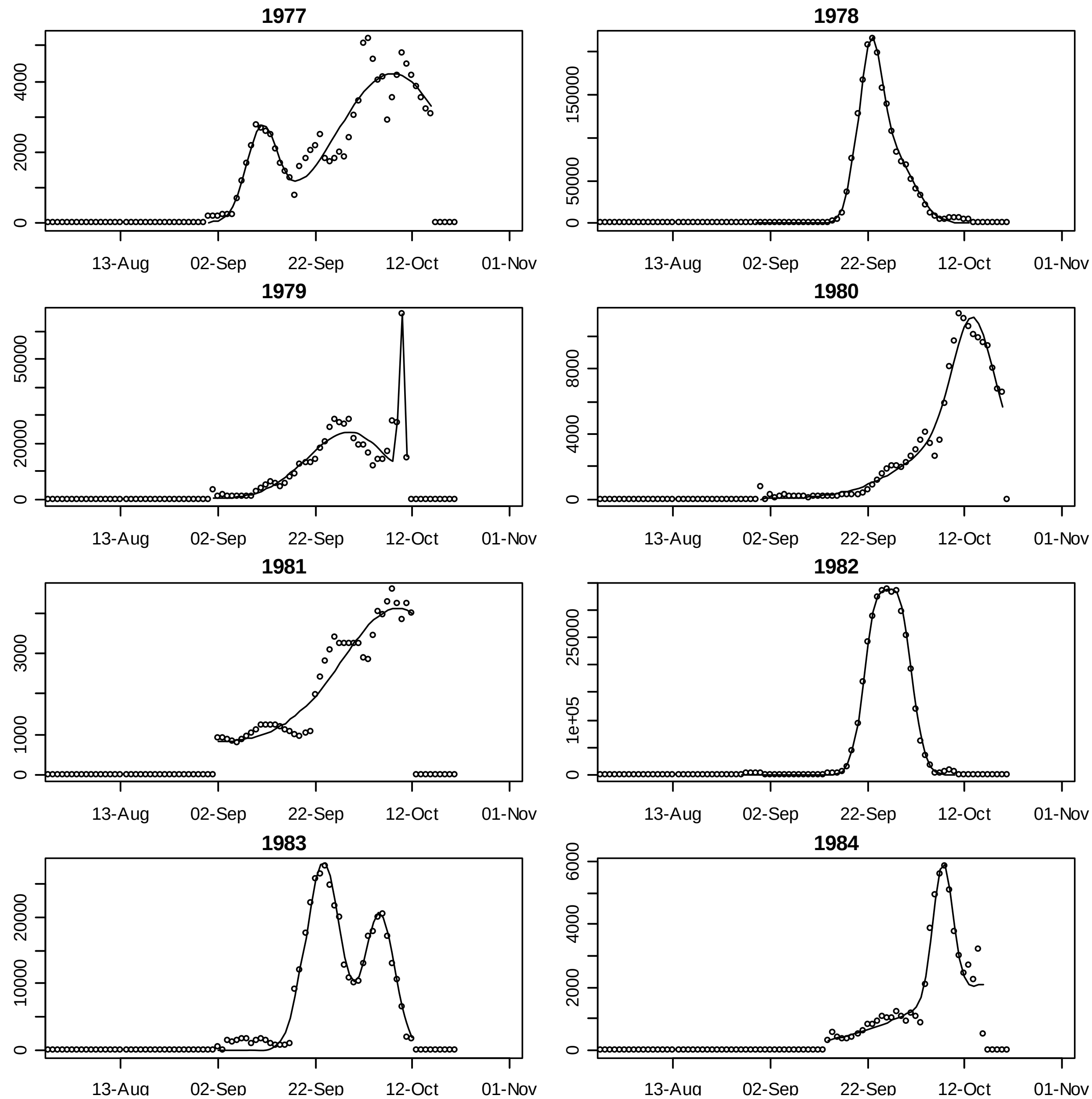

Figure B4a. Late run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years. with the exception of 1998 (normal), 2000 (gamma) and 2004 (normal).

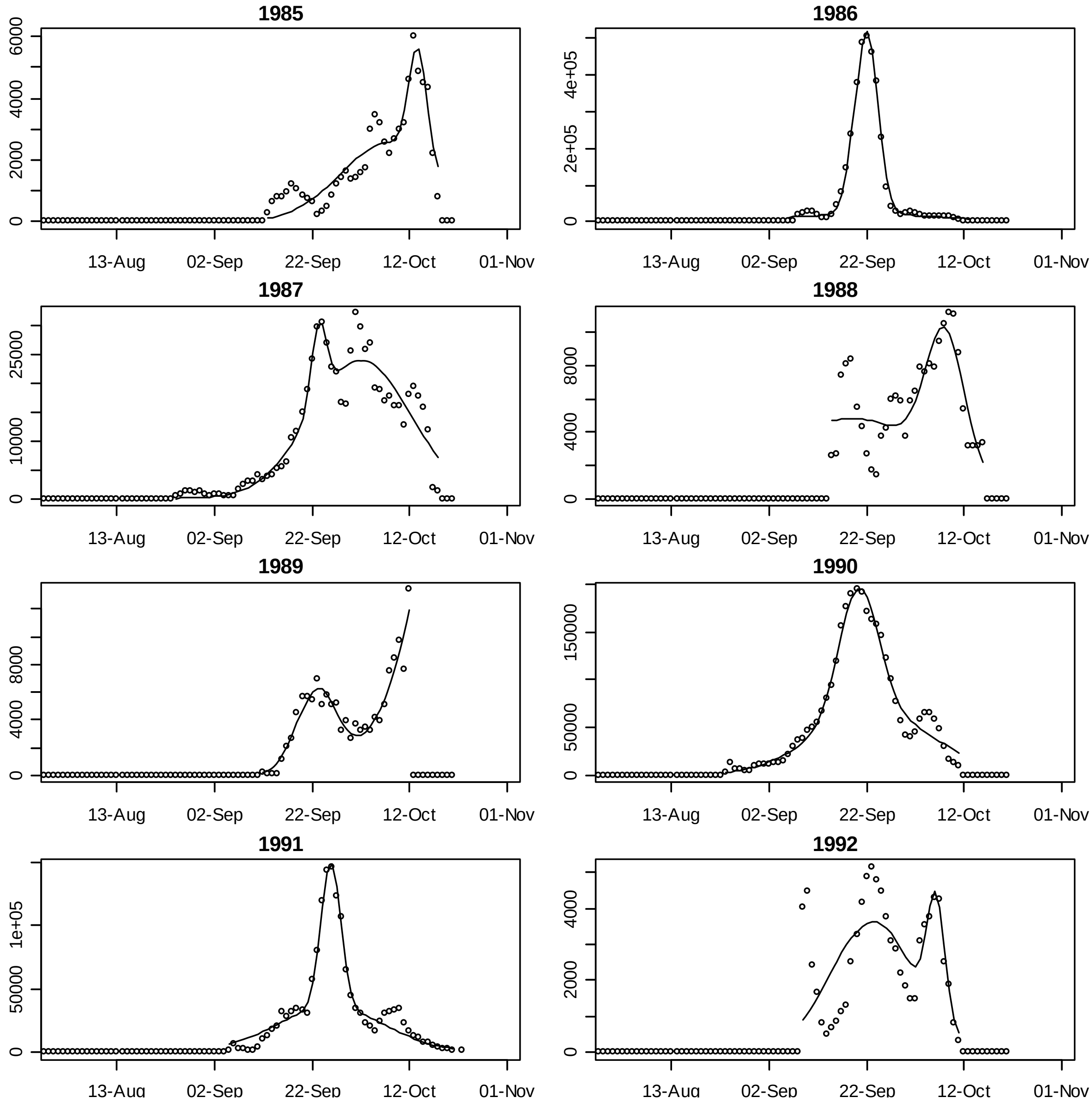

Figure B4b. Late run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1998 (normal), 2000 (gamma) and 2004 (normal).

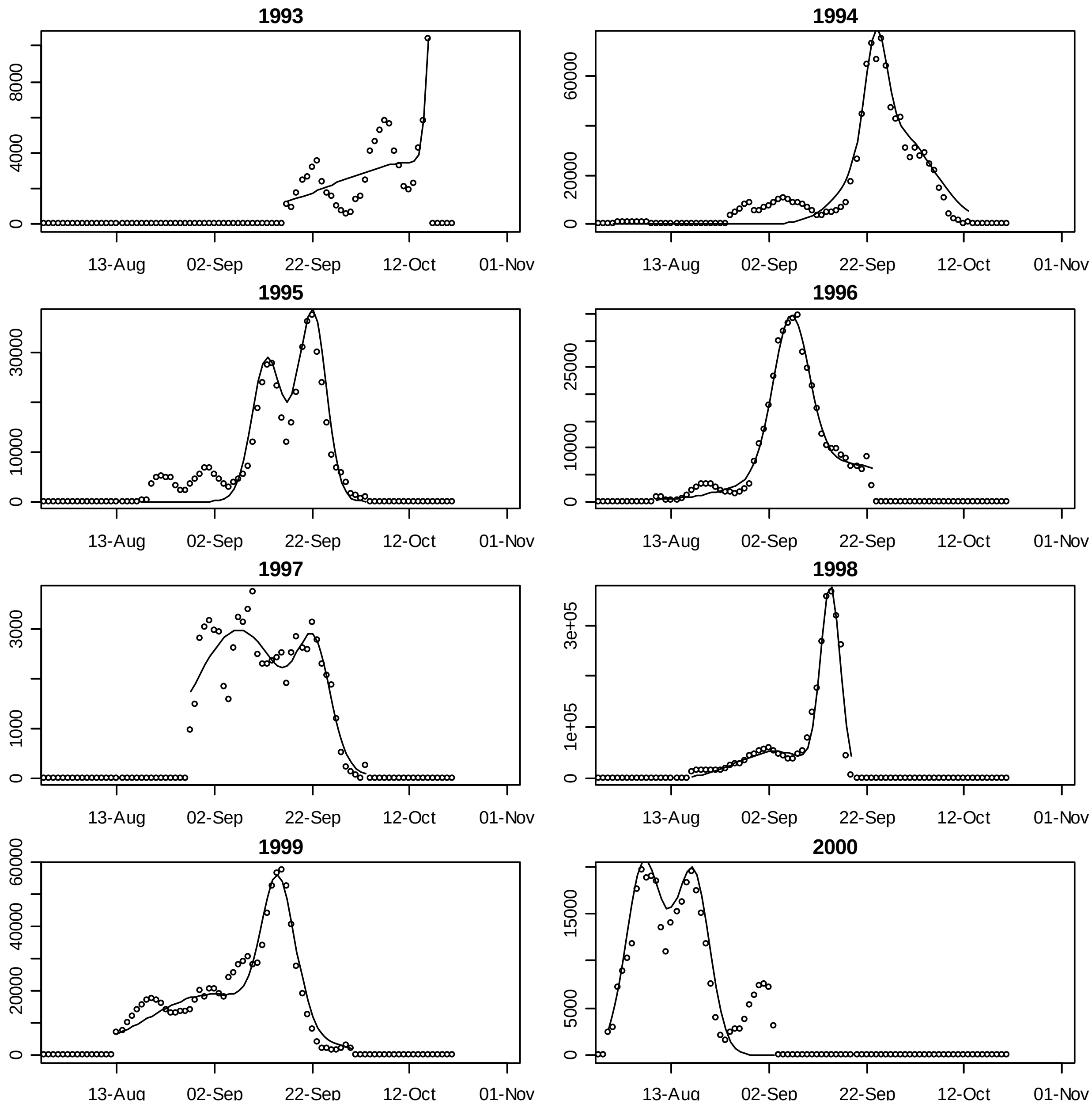

Figure B4c. Late run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1998 (normal), 2000 (gamma) and 2004 (normal).

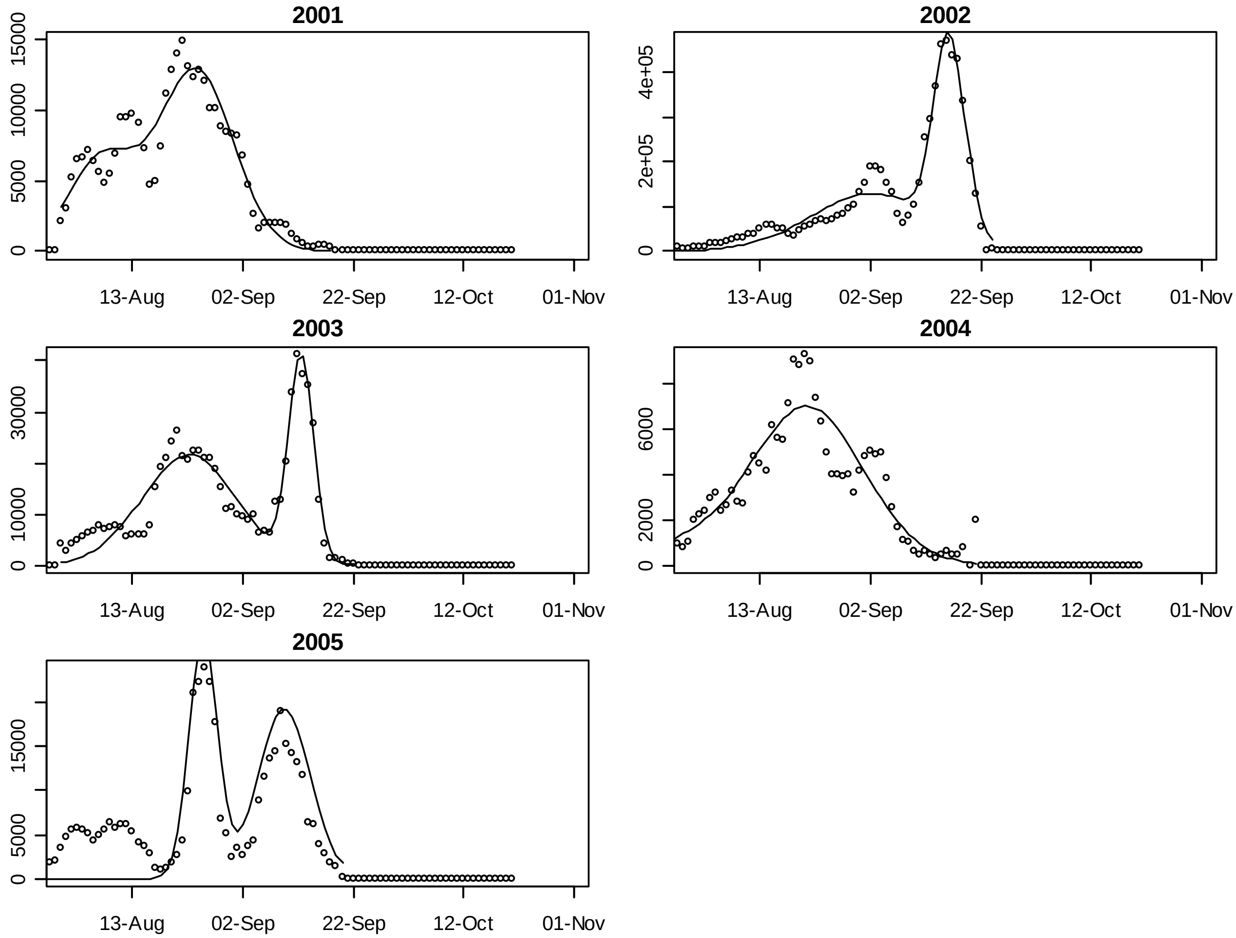

Figure B4d. Late run profile distributions from 1977 – 2005. Open points consist of 5-day moving averages applied to Mission hydroacoustic estimates. The black line is the best-fit mixed normal distribution. AIC values indicated that the mixed normal distribution was a best-fit to the data in all years with the exception of 1998 (normal), 2000 (gamma) and 2004 (normal).

Table B1. A summary of results from a model fitting procedure applied to daily Mission Early Stuart-run profile data smoothed with a 5-day moving average. Four models were fit to the data: normal, log normal, gamma and mixed normal (two combined normal distributions). Bolded values indicate minimum AIC values (best-fit model).

Year	**AIC**				**Best-fit model**	**Best-fit mixed normal model parameters**				
	Normal	**Log normal**	**Gamma**	**Mixed normal**		$\overline{C}$	σ_1	k	σ_2	p
1977	20.68	20.96	20.85	**19.77**	mixed	8.80	2.30	8.89	2.91	0.35
1978	16.40	18.35	17.83	**16.17**	mixed	2.50	2.24	7.66	5.06	0.12
1979	19.09	18.86	18.93	**18.21**	mixed	10.33	3.69	0.19	8253	0.00
1980	15.83	15.92	15.75	**15.66**	mixed	5.53	3.17	8.59	3.71	0.59
1981	19.22	19.51	19.34	**19.10**	mixed	16.47	3.20	1.01	7.72	0.24
1982	17.30	17.40	17.38	**17.25**	mixed	12.99	4.30	9.90	3.16	0.72
1983	17.77	17.40	17.37	**16.41**	mixed	9.35	3.62	11.09	3.73	0.71
1984	16.78	16.22	16.38	**14.31**	mixed	10.81	1.91	6.98	8.70	0.29
1985	19.68	19.80	19.75	**16.93**	mixed	9.21	4.17	14.24	4.41	0.44
1986	15.22	15.13	**14.85**	14.88	gamma	9.19	4.12	0.84	13.93	0.26
1987	16.67	17.97	17.54	**16.64**	mixed	8.15	3.20	9.79	6.69	0.10
1988	17.69	18.25	17.94	**17.68**	mixed	3.51	63.75	10.97	5.72	0.57
1989	21.16	20.56	20.73	**20.08**	mixed	11.02	3.07	11.78	6.39	0.47
1990	17.43	18.19	17.94	**15.96**	mixed	15.72	8.26	1.08	2.64	0.77
1991	18.46	19.39	19.03	**18.15**	mixed	11.07	2.03	10.90	7.31	0.07
1992	19.26	20.09	19.88	**17.76**	mixed	15.66	12.11	5.06	3.21	0.73
1993	20.53	21.06	20.87	**20.36**	mixed	14.61	4.75	8.31	4.05	0.33
1994	17.95	18.73	18.53	**17.12**	mixed	17.62	8.32	2.12	3.24	0.66
1995	**17.23**	17.65	17.46	17.36	normal	15.68	3.43	5.52	2.59	0.79
1996	16.38	17.36	17.09	**15.66**	mixed	16.89	6.65	3.34	3.58	0.33
1997	21.56	22.39	22.18	**19.79**	mixed	17.25	5.49	11.93	4.89	0.29
1998	17.93	18.85	18.59	**16.79**	mixed	11.97	4.82	8.52	3.37	0.49
1999	18.37	17.69	17.74	**17.07**	mixed	7.67	1.83	3.48	5.92	0.22
2000	18.75	18.55	18.43	**17.04**	mixed	14.39	4.63	10.21	3.75	0.62
2001	**17.86**	18.59	18.37	17.94	normal	15.74	14.25	6.65	7.49	0.23
2002	16.23	16.73	16.59	**15.25**	mixed	13.93	6.15	8.02	2.06	0.79
2003	15.40	16.00	15.88	**13.82**	mixed	5.70	5.81	8.78	2.89	0.42
2004	17.18	17.51	17.35	**15.94**	mixed	14.37	5.53	11.67	3.88	0.58
2005	18.12	18.30	18.23	**17.60**	mixed	4.88	147	23.15	4.50	0.72

Table B2. A summary of results from a model fitting procedure applied to daily Mission Early Summer-run profile data smoothed with a 5-day moving average. Four models were fit to the data: normal, log normal, gamma and mixed normal (two combined normal distributions). Bolded values indicate minimum AIC values (best-fit model).

Year	AIC				Best-fit model	Best-fit mixed normal model parameters				
	Normal	Log normal	Gamma	Mixed normal		$\overline{C}$	σ_1	k	σ_2	p
1977	17.72	17.74	17.73	**16.32**	mixed	21.83	1.85	0.06	2.3e4	0.00
1978	17.74	17.91	17.86	**16.10**	mixed	29.29	18.75	7.74	3.00	0.67
1979	19.40	19.48	19.41	**19.39**	mixed	17.20	3.15	8.28	5.87	0.25
1980	17.90	17.97	17.95	**16.17**	mixed	25.72	9.55	0.02	1.99	0.64
1981	17.65	17.74	17.71	**17.19**	mixed	20.31	1.95	8.21	3.72	0.35
1982	19.16	19.42	19.34	**17.60**	mixed	27.08	14.68	8.79	1.92	0.73
1983	19.63	19.52	19.55	**17.81**	mixed	18.09	3.61	20.24	6.93	0.43
1984	17.77	17.61	17.62	**17.45**	mixed	18.65	4.04	5.67	10.65	0.51
1985	**16.59**	16.79	16.72	16.61	normal	23.64	9.18	15.94	7.97	0.31
1986	18.74	18.67	18.70	**17.31**	mixed	35.53	8.94	0.00	2.68	0.60
1987	20.58	20.25	20.36	**19.35**	mixed	29.07	3.43	7.56	12.91	0.40
1988	20.86	21.15	21.07	**20.00**	mixed	26.55	8.94	4.10	1.70	0.80
1989	17.91	17.99	17.97	**17.15**	mixed	28.82	2.29	4.73	14.00	0.32
1990	22.18	22.26	22.22	**22.11**	mixed	29.33	2.11	10.80	5.15	0.21
1991	20.81	20.57	20.60	**20.49**	mixed	24.75	4.34	7.82	17.14	0.24
1992	19.21	19.60	19.47	**18.74**	mixed	24.43	10.41	2.16	4.31	0.55
1993	14.85	15.18	15.09	**13.95**	mixed	14.33	2.85	13.40	4.46	0.16
1994	20.98	21.16	21.10	**20.54**	mixed	31.35	10.53	9.11	1.51	0.86
1995	17.40	18.09	17.88	**16.68**	mixed	30.34	8.17	9.25	4.66	0.76
1996	19.89	20.16	20.07	**19.64**	mixed	30.19	10.15	1.43	2.00	0.87
1997	18.07	18.00	18.01	**17.69**	mixed	33.59	10.69	17.36	1.81	0.02
1998	20.45	20.58	20.53	**20.44**	mixed	21.98	3.35	12.41	6.76	0.18
1999	18.01	18.89	18.64	**17.06**	mixed	29.03	10.06	3.87	5.09	0.49
2000	21.13	21.44	21.34	**18.84**	mixed	25.94	7.81	11.22	2.29	0.74
2001	18.70	18.65	**18.62**	18.71	gamma	26.31	8.74	18.32	21.00	0.21
2002	18.90	19.54	19.32	**18.80**	mixed	23.64	10.04	8.46	5.86	0.14
2003	19.37	19.12	19.20	**18.94**	mixed	29.81	6.80	29.12	5.69	0.59
2004	**19.83**	20.54	20.27	19.90	normal	19.84	18.79	10.29	11.34	0.00
2005	21.08	21.10	21.10	**20.65**	mixed	62.29	3.96	14.11	4.58	0.58

Table B3. A summary of results from a model fitting procedure applied to daily Mission Summer-run profile data smoothed with a 5-day moving average. Four models were fit to the data: normal, log normal, gamma and mixed normal (two combined normal distributions). Bolded values indicate minimum AIC values (best-fit model).

Year	AIC				Best-fit model	Best-fit mixed normal model parameters				
	Normal	Log normal	Gamma	Mixed normal		$\overline{C}$	σ_1	k	σ_2	p
1977	21.99	21.87	21.91	**19.64**	mixed	18.08	1.92	8.54	7.95	0.73
1978	20.94	20.92	20.92	**19.33**	mixed	24.82	4.11	14.87	2.87	0.57
1979	22.00	22.17	22.10	**21.45**	mixed	17.22	1.47	0.00	9.08	0.20
1980	22.11	22.49	22.37	**21.13**	mixed	17.81	7.19	6.81	1.60	0.78
1981	24.13	23.92	23.99	**22.14**	mixed	22.79	2.58	13.27	4.20	0.56
1982	21.35	21.32	21.34	**20.58**	mixed	26.03	12.16	1.14	2.25	0.66
1983	19.79	20.06	19.92	**19.54**	mixed	16.49	1.28	4.91	6.46	0.05
1984	22.93	22.91	22.93	**22.60**	mixed	25.36	11.00	6.17	1.48	0.82
1985	24.31	24.38	24.36	**22.53**	mixed	36.38	11.44	2.85	1.92	0.64
1986	21.95	21.60	21.67	**21.18**	mixed	23.45	6.18	13.31	1.81	0.87
1987	21.15	21.31	21.24	**20.79**	mixed	30.87	8.42	9.91	2.50	0.86
1988	21.71	21.92	21.84	**20.40**	mixed	16.47	2.73	8.74	2.64	0.40
1989	24.82	24.89	24.87	**24.62**	mixed	13.56	6.05	15.79	4.94	0.27
1990	23.30	23.38	23.31	**23.24**	mixed	35.24	8.69	15.41	4.98	0.76
1991	22.90	22.89	22.87	**22.57**	mixed	17.37	4.48	17.55	7.94	0.35
1992	21.24	21.49	21.36	**20.37**	mixed	22.55	1.41	10.54	8.44	0.08
1993	25.31	25.62	25.53	**23.56**	mixed	27.58	6.70	18.09	4.82	0.36
1994	24.34	24.17	24.21	**23.81**	mixed	20.13	1.75	9.66	8.97	0.18
1995	22.33	22.79	22.66	**20.88**	mixed	24.34	9.91	5.18	1.93	0.83
1996	23.15	23.46	23.35	**22.71**	mixed	17.06	2.52	11.11	4.55	0.20
1997	25.64	25.74	25.72	**23.32**	mixed	29.19	13.65	4.67	2.03	0.68
1998	24.73	25.01	24.88	**24.19**	mixed	24.52	11.10	13.20	1.75	0.89
1999	21.59	22.03	21.79	**20.38**	mixed	21.49	5.44	17.51	8.88	0.32
2000	22.16	22.55	22.43	**21.40**	mixed	27.90	7.23	7.05	1.82	0.87
2001	23.56	24.19	23.97	**23.09**	mixed	32.28	11.00	7.54	1.82	0.94
2002	23.49	23.64	23.47	**22.52**	mixed	29.32	4.61	14.34	9.21	0.23
2003	22.74	23.04	22.93	**20.57**	mixed	33.13	6.85	17.75	5.20	0.47
2004	20.20	20.86	20.52	**20.12**	mixed	24.56	4.22	11.36	8.25	0.13
2005	25.49	25.36	25.41	**24.04**	mixed	41.25	3.93	12.86	3.30	0.68

Table B4. A summary of results from a model fitting procedure applied to daily Mission Late-run profile data smoothed with a 5-day moving average. Four models were fit to the data: normal, log normal, gamma and mixed normal (two combined normal distributions). Bolded values indicate minimum AIC values (best-fit model).

Year	AIC				Best-fit model	Best-fit mixed normal model parameters				
	Normal	Log normal	Gamma	Mixed normal		$\overline{C}$	σ_1	k	σ_2	p
1977	17.25	17.27	17.27	**17.14**	mixed	32.45	22.01	7.12	6.53	0.75
1978	23.02	22.32	22.58	**20.10**	mixed	24.44	2.42	4.92	4.27	0.57
1979	21.83	21.79	21.79	**20.27**	mixed	28.68	8.53	11.19	0.55	0.86
1980	17.71	17.98	17.90	**16.95**	mixed	42.74	12.15	2.14	4.34	0.55
1981	15.85	16.11	16.14	**15.76**	mixed	1.66	27.04	36.91	12.18	0.31
1982	22.91	23.06	22.94	**20.28**	mixed	28.22	2.30	5.04	2.76	0.40
1983	20.88	20.62	20.70	**18.17**	mixed	22.55	3.50	11.70	3.13	0.61
1984	17.08	17.20	17.17	**15.86**	mixed	24.57	2.04	15.24	19.83	0.17
1985	17.19	17.37	17.34	**16.41**	mixed	25.75	9.96	6.00	1.87	0.79
1986	23.80	24.13	24.01	**22.42**	mixed	16.90	2.30	1.53	15.88	0.78
1987	20.62	20.52	20.53	**20.18**	mixed	30.25	1.62	8.83	10.27	0.08
1988	19.23	19.33	19.33	**18.22**	mixed	4.35	1.90	17.87	6.91	0.20
1989	18.75	18.81	18.81	**17.11**	mixed	11.96	4.05	68.02	18.40	0.00
1990	23.65	23.57	23.57	**22.43**	mixed	28.37	3.96	3.21	12.28	0.40
1991	23.62	23.58	23.61	**21.62**	mixed	21.76	11.18	0.00	2.06	0.63
1992	18.06	18.15	18.18	**17.98**	mixed	15.25	8.50	12.95	1.84	0.83
1993	18.30	18.34	18.45	**18.04**	mixed	27.59	18.65	18.50	3.71	0.00
1994	22.26	22.16	22.20	**21.51**	mixed	54.78	2.21	3.95	7.73	0.26
1995	21.22	21.39	21.34	**20.66**	mixed	26.88	3.10	9.09	2.82	0.45
1996	19.94	19.56	19.69	**19.18**	mixed	28.47	15.76	0.49	3.94	0.41
1997	16.63	16.93	16.79	**16.13**	mixed	11.07	9.68	15.34	3.21	0.82
1998	**25.34**	25.46	25.42	25.52	normal	29.36	2.91	11.08	0.97	0.55
1999	22.47	22.88	22.78	**20.41**	mixed	21.21	13.17	13.24	2.79	0.69
2000	20.10	19.90	**19.87**	20.06	gamma	8.40	3.71	9.80	3.44	0.53
2001	19.17	20.02	19.78	**18.65**	mixed	7.98	5.75	17.16	6.99	0.29
2002	26.80	26.88	26.86	**24.50**	mixed	57.15	11.03	14.15	2.75	0.54
2003	22.20	22.23	22.22	**20.15**	mixed	24.19	8.51	20.47	2.29	0.67
2004	**18.05**	18.35	18.23	18.11	normal	9.22	6.22	23.02	10.40	0.05
2005	21.26	21.36	21.33	**20.80**	mixed	37.71	2.61	14.83	4.78	0.44

APPENDIX C: RUN TIMING OCEANOGRAPHIC FORECAST MODEL

Blackbourn (1987) demonstrated that a large percentage of the variation in annual run timing for most Fraser River sockeye stocks is dependent on Gulf of Alaska sea surface temperatures (SST). The influence of Alaskan currents on migrating timing was analysed in Thomson et al. 1994. Currently, pre-season 50% dates for Early Stuart and Chilko run groups are calculated as a function of observed Alaskan sea surface temperatures and forecasted eastward sea currents using a simple multiple regression model developed by D.J. Blackbourn (M. Folkes, DFO, Nanaimo, pers. comm. 2006). The Ocean Surface Current Simulations (OSCURS) model (Thomson et al. 1994) was created by a now-retired NOAA scientist (Dr. W.J. Ingraham), and will likely become defunct after this year. The Early Stuart model predicts the 50% date at Patullo Bridge (Surrey, BC), while the Chilko model predicts the Area 20 (Juan de Fuca Strait) date.

Summer-run 50% dates are estimated using the Chilko forecast and the anticipated abundance and historic timing of other Summer-run stocks. The difference between Early Stuart and Summer 50% dates, and Early Summer and Late 50% dates are then used to make forecasts for the latter two run groups (I. Guthrie, PSC, pers. comm. 2007). In this report, only 50% forecasts for the Early Stuart run, illustrating direct use of the multiple regression model, are provided as an example.