THE IMPACT OF MANAGEMENT OBJECTIVES AND PERFORMANCE MEASURES ON MODEL SELECTION FOR FRASER RIVER SOCKEYE SALMON

by

Jonathan Wellesley Cummings
B.A., Oberlin College, 2005

RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF RESOURCE MANAGEMENT

In the
School of Resource and Environmental Management
Project Number 477

SIMON FRASER UNIVERSITY

Summer 2009

APPROVAL

Name:	**Jonathan Wellesley Cummings**
Degree:	**Master of Resource Management**
Title of Project:	**The Impact of Management Objectives and Performance Measures on Model Selection for Fraser River Sockeye Salmon**
Project No.:	**477**
Examining Committee:	
Chair:	**Merran Hague** Biologist, Salmon and Freshwater Ecosystems Fisheries & Oceans Canada
	Dr. Randall Peterman Senior Supervisor Professor, School of Resource and Environmental Management Simon Fraser University
	David Patterson Supervisor Research Biologist, Freshwater Ecosystems Section Fisheries & Oceans Canada
	Dr. Duncan Knowler Supervisor Associate Professor, School of Resource and Environmental Management Simon Fraser University

Date Defended/Approved: July-22-2009

ABSTRACT

Fisheries management entails decision making in the face of complex, uncertain systems, often resulting in decisions with imperfect outcomes that fail to achieve management objectives. For Fraser River sockeye salmon (*Oncorhynchus nerka*), fishery managers use models to better anticipate the magnitude of in-river loss of adults migrating upstream to spawn, thereby improving the chance of avoiding conservation concerns or losing fisheries revenue. Ecosystem-based models (Management Adjustment (MA) models), which predict in-river loss from forecasts of river environmental conditions, provide management advice on appropriate harvest adjustments (in terms of reduced catch) to increase the probability of achieving spawning escapement targets. The performance of a suite of MA model structures and predictor variables was assessed using a retrospective analysis and a range of asymmetric loss functions. Rank order of best models depended on the performance measures chosen, the relative importance of specific management objectives, and the degree of asymmetry in loss functions.

Keywords: Fraser River, sockeye salmon, management adjustment, model selection, performance measures, management objectives, asymmetric loss functions, retrospective analysis

OVERVIEW

Managing Fraser River sockeye salmon (*Oncorhynchus nerka*) to achieve spawning escapement targets involves the difficult task of appropriately limiting harvest to account for mortality during the upstream migration of adult salmon later in the season. Therefore, the management of Fraser River sockeye salmon relies on the timely forecasting of both precise and unbiased estimates of in-river loss, which is calculated as the number of sockeye salmon that are estimated at the lower Fraser River at the Mission hydroacoustic facility minus the number that are estimated to arrive at the spawning grounds in the upper Fraser River to reproduce. While a number of models have been used to adjust the harvest of sockeye salmon to account for in-river loss, this research expands upon that work by providing a formal model selection framework that entails identifying the models to evaluate, exploring the performance of alternative forecasting techniques, conducting a retrospective analysis, and ranking the models using a set of five performance measures. This framework was also used to evaluate the performance of three alternative forecasting techniques that either combine multiple models to make a single forecast or use forecasted conditions to select a single model based on those forecasted conditions each year. The second chapter extends this work by going beyond the standard assumption of symmetric cost functions in model selection by considering the effect of asymmetric loss on model rank. One key finding is that not using the available environmental and biological information to model the in-river loss of Fraser river sockeye salmon results in greater discrepancies between spawning outcomes and spawning targets than results when that information is used to make predictions about in-river loss. Also, for two of the four run-timing groups (Early Stuart and Late), a single model (the Early Stuart historic model and Run-timing model for the Late run-timing group) performs best for at least four of the five performance measures, indicating that managers can be fairly confident that selecting the best run-timing-group-specific model will likely result in the best available outcome for those two groups. However, the conclusions for the two remaining run-timing groups (Early Summer and Summer) is less clear, indicating that careful decision making and clarification of management objectives can aid the model selection process and improve the likelihood of more closely achieving Fraser River fisheries objectives. In addition, I found that using asymmetric loss functions to rank models caused model rank to change from the baseline assumption of symmetry, depending on the degree of asymmetry in those functions. Therefore, management of Fraser River sockeye salmon can also be improved through consideration of appropriate asymmetric loss functions that represent sockeye salmon management objectives and by selecting models accordingly.

To the feeling of awe we all achieve when viewing the power of life to adapt and flourish and to everyone with whom I have shared that awe.

&

As Vladimir Karpenko expressed

To my employer **The Salmon**

ACKNOWLEDGEMENTS

Thank you to everyone who supported me along the way. Thank you to my committee members, Duncan Knowler, David Patterson, and Randall Peterman; your guidance is most appreciated. Thank you as well to Merran Hague who also greatly contributed to this project. Thank you to everyone in the School of Resource and Environmental Management and to my fisheries cohort; we learned a lot together. Finally, thank you to Lauren Kordonowy and Bailey for their support both in and out of the office. Support for this work was provided by the Southern Boundary Restoration and Enhancement Fund and Fisheries and Oceans Canada's Fraser River Environmental Watch program.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

GLOSSARY

Difference Between Estimates (DBE)	Difference between the upriver spawning ground abundance estimate and the lower-river Mission hydroacoustic abundance estimate. Expressed as the natural log of the quantity spawning escapement divided by the Mission potential spawning escapement for a specific aggregate of fish.
En-route mortality	Sockeye that die during their migration in the Fraser River prior to reaching their spawning grounds.
In-river loss	Sockeye that are estimated in the lower Fraser River at the Mission hydroacoustic facility that are not estimated on the spawning grounds. Includes both en-route mortality and observation error.
Management Adjustment (MA)	The amount of catch by which fisheries managers reduce the target harvest downstream of Mission to account for the in-river loss of sockeye salmon during their adult Fraser River migration.
Management adjustment model	A mathematical formula or set of formulas to determine the management adjustment, often based upon environmental conditions.
Mission	Site of abundance estimation in the lower Fraser River.
Potential Spawning Escapement (PSE)	Salmon that escape capture by fishing gear prior to reaching Mission in the lower Fraser River minus the forecasted in-river catch above Mission.
Retrospective analysis	A means of measuring how well a forecasting model would have performed for each year if it had been used historically by comparing the forecasted value of an indicator or variable obtained from data up to the year of the forecast with the actual value.
Run/ Run group/ Run-timing Group	One of the four major aggregates of sockeye salmon stocks, grouped for management purposes due to their historical migration as a cohesive group in terms of return dates (run-timing). (Early Stuart, Early Summer, Summer, Late)
Run-timing	The date during the year when 50% of the stock of adult sockeye has reached a particular point (Hells Gate near Hope, BC) during their upstream migration.
Spawner	A fish that reaches its spawning location and is counted by Fisheries and Oceans Canada's Stock Assessment Division.
Spawning Escapement (SE)	Salmon that escape both capture in the fishery and death during migration and are thereby enumerated when the reach the spawning grounds (Note: not all of these will necessarily reproduce; many die on the spawning grounds without spawning).
Stock	A grouping of aquatic organisms (similar to a population) for management purposes. In this case, a grouping of sockeye salmon that is based upon their timing of entry of adults migrating upstream into the Fraser River system.

TABLE OF SYMBOLS

Symbol	Description
SE	Spawning escapement abundance estimate
PSE	Potential spawning escapement abundance estimate
DBE	Difference Between Estimates: natural log of the ratio of spawning escapement abundance estimate divided by the potential spawning escapement estimate
T	Fraser River Temperature: 31-day mean measured in degrees Celsius at Qualark, centered on the 50% run-timing date.
Q	Fraser River Discharge: 31-day mean water flow rate measured in cubic meters per second at Hope, centered on the 50% run-timing date.
D_{50}	50% run-timing date: The day of the year when 50% of a stock has reached Hells Gate.
H	Historical DBE: The average historically observed DBE.
RE	Raw error: The forecasted minus the observed DBE on the linear scale
N	Number of years of an analysis
i	Model number
j	Performance measure
W	AIC_c model weight
OW	Optimized model weight
MRE	Mean Raw Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
R^2	Adjusted R-squared
AIC_c	Akaike's Information Criterion for small samples
ΔAIC_c	Delta AIC_c: a model's AIC_c score minus that of the best-ranked model based on AIC_c

CHAPTER 1: RETROSPECTIVE EVALUATION

Introduction

Fisheries managers face the difficult task of trying to meet multiple, at times competing, objectives by regulating complex human behaviors within complicated natural systems that have intricate feedback dynamics. Managers are tasked with managing fisheries to meet society's wishes, such as increasing opportunities for income, employment, cultural identification, productive ecosystems, recreation, and sustenance. Achievement of some of these desired outcomes must often come at the expense of achieving others.

Numerous international agreements and Canadian policies list some form of sustainability as a primary objective of fisheries management (e.g., *Wild Salmon Policy*, *Fisheries Act*). Naturally, because of the trade-off between meeting spawning targets and fulfilling harvest allocation requests, the greater the emphasis on spawning objectives, the less likely it is that numerous harvest requests from various fishing sectors can be met. After determining the desired level of those trade-offs and establishing objectives of a fishery as a whole, managers of Pacific salmon (*Oncorhynchus spp*.) choose spawning targets that balance spawning and allocation in an effort to meet those objectives. However, given the uncertainty in natural systems, and the corresponding uncertainty about the effectiveness of management efforts in these complex systems, there can be considerable discrepancy between spawning targets and actual spawner abundance at the end of each year. Therefore, efforts to improve the ability to forecast these complex system dynamics should aid in meeting spawning targets and thereby in meeting fisheries objectives.

The British Columbia Fraser River sockeye salmon (*Oncorhynchus nerka*) fishery (Fig. 1-1) is the largest salmon fishery in Canada, averaging annual catches of 5.5 million fish over the previous 50 years (Pacific Salmon Commission; PSC, 2009). These salmon are of great importance both as a fishable product, providing the backbone of the Canadian commercial salmon fishery (Roos 1991), and as a social and cultural resource to both First Nations and residents of British Columbia. Given the importance of sockeye salmon to British Columbia as an environmentally and economically sustainable resource, sustainable management is of great importance.

To ensure the sustained presence of Fraser sockeye salmon, Fisheries and Oceans Canada (DFO) and the bi-lateral Fraser River Panel (the governing body formed by Canada and the United States of America to jointly manage Fraser River salmon) manage with the goal of achieving spawning escapement targets and catch allocation goals as laid out in the 1985 *Pacific Salmon Treaty* (Shepard and Argue 2005). Large in-river losses of adults i.e., sockeye salmon that are lost during upriver migration toward spawning grounds, are a major factor that negatively affects this fishery both in terms of meeting conservation (i.e., spawning escapement targets) and allocation (i.e., First Nations, commercial, and recreational catch) objectives (Cooke et al. 2004, Patterson et al. 2007b). For example, estimates of in-river loss have exceeded a half-million fish in 8 of the past 16 years. Such events are commonly associated with extreme environmental conditions during migration (Patterson et al. 2007b). Underestimates of the in-river loss can lead to conservation concerns with too few fish reaching spawning grounds due to excess catches, whereas overestimates of in-river loss can result in foregone catch (Table 1-1). Therefore, effective management of the Fraser River sockeye salmon fishery depends, in part, on precise and unbiased predictions of in-river loss.

To predict these in-river losses, biologists currently use management adjustment (MA) models to predict differences between lower-river (near Mission, BC) and up-river (spawning ground) sockeye salmon escapement estimates (difference between estimates, DBEs), after adjusting for expected in-river catch, for each stock (Table 1-1, Fig. 1-1). Those DBEs are estimated as a function of Fraser River environmental conditions such as water temperature and flow rate (Macdonald et al. 2009, in review). For management purposes, returning stocks are divided into four major management groups based on their historical return times to the river: (1) Early Stuart, (2) Early Summer, (3) Summer and (4) Late-run (Fig. 1-1) (Gable and Cox-Rogers 1993). These stock-specific in-river loss predictions are then used to provide management advice on appropriate MAs to apply to the harvest (i.e., reductions in allowable catch) in order to increase the probability of achieving spawning escapement targets (Hague and Patterson 2007, Macdonald et al. 2009, in review). The larger the MA, the greater the reduction in catch and hence the greater the number of fish that are allowed to pass upstream of Mission. Forecasting appropriate MAs is difficult because in-river loss is not only affected by en-route mortality resulting from detrimental environmental conditions, but also by potential measurement error for adult salmon abundance in both lower river and spawning ground escapement estimates, uncertain catch estimates, and unreported harvest.

Several MA models have been applied historically by DFO and PSC biologists (Macdonald et al. 2009, in review). The simplest approach assumes the MA should be similar to the average of the historical annual differences between estimates (DBEs) of the lower- (Mission) and up-river (spawning ground) abundances. To better reflect sockeye salmon migration conditions, biologists have also used ecosystem-based models based upon the well-recognized correlation between high river temperatures and increased en-route mortality of salmon (Naughton et al. 2005, Richter and Kolmes 2005, Keefer et al. 2008), and such effects have also been observed in the Fraser River (Macdonald 2000, Macdonald et al. 2000, Cooke et al. 2004, Rand et al. 2006, Crossin et al. 2008, Farrell et al. 2008). In addition, research suggests that temperature effects are stock-specific (Lee et al. 2003, Farrell et al. 2008), supporting use of MA models specific to each run-timing group to capture stock-specific variability (Macdonald et al. 2009, in review).

Studies have also shown other effects as well. For instance, increased Fraser River velocity, which is associated with increased discharge, causes greater energy usage in upstream-migrating adult salmon (Hinch and Rand 1998, Hinch et al. 2002, Standen et al. 2002, Rand et al. 2006), which is associated with high en-route mortality (Hinch et al. 1996, Rand and Hinch 1998, Hinch and Bratty 2000, Macdonald et al. 2000, Rand et al. 2006). Recent extreme shifts to earlier arrival timing for Late-run sockeye salmon (Lapointe et al. 2003, Cooke et al. 2004, Crossin et al. 2007, Cooke et al. 2008), have resulted in dramatic increases in duration of freshwater residence as well as an increase in the temperature and discharge experienced. Not surprisingly, such early-entry Late-run migrants experience higher rates of in-river mortality than their late-entry counterparts (Cooke et al. 2004, English et al. 2005, Young et al. 2006, Crossin et al. 2007).

Therefore, since 2001, MA models developed by the PSC and DFO (Hague and Patterson 2007, Macdonald et al. 2009, in review) have fit historical DBEs to average Hells Gate river temperature and Hope discharge values to forecast MAs for Early Stuart, Early Summer, and Summer sockeye salmon run-timing groups. An additional model that is typically applied to MA forecasts for Late-run sockeye salmon utilizes the forecasted date at which 50% of a run-timing group reaches Hells Gate near Hope, five days after reaching the Mission hydroacoustics facility (English et al. 2005, Hanson et al. 2008).

Despite the wide variety of such management adjustment models that have either been proposed or applied in the past to help managers estimate appropriate management adjustments, there has been little comprehensive analysis that quantitatively compares the statistical performance of these methods at achieving management objectives. My research objective was to develop such a standardized framework to easily evaluate performance of new models and/or incorporate additional years of data. This work will fill this gap and help streamline pre-season (and in-season) planning for these sockeye salmon fisheries with respect to selection of MA models. My framework is based on retrospective analysis (which uses historical data) of a suite of alternative MA models and explores how management objectives, represented by five different performance measures, can influence rankings of those models. Appropriate performance measures act as indicators of achievement for management objectives. Therefore, using this framework to examine MA model performance as a function of multiple performance measures provides an indication of the performance of the suite of MA models for a range of management objectives. By aiding the management adjustment process, this model-assessment framework will also stimulate discussions among scientists and managers to help the latter articulate objectives of the Fraser River sockeye salmon fisheries. Thus, managers will be more likely to achieve spawning escapement targets and thereby increase the probability of attaining sustainable catch allocations. Managers will also be more likely to receive science advice tailored to their particular situations and scientists will be better able to focus research on areas where it can be of greatest use.

Retrospective Analysis

Retrospective analysis, the main method of analysis used here, is a cross validation technique (Shao 1993) that uses historical data up to a given year to fit various forecasting models, and then iteratively re-fits the model with each additional year of data and compares annual forecasts to annually observed actual values. The performance of each model is then summarized over the entire time period of analysis. In fisheries research, retrospective methods have previously been used to evaluate a variety of forecasting models, such as forecasts of salmon abundance (Wood et al. 1997, Peters et al. 2001, Holt and Peterman 2004, Haeseker et al. 2005, Cass et al. 2006, Haeseker et al. 2008), and annual harvests of Atlantic menhaden (*Brevoortia tyrannus*) (Hanson et al. 2006).

In my study, a retrospective analysis was conducted to rank a suite of six potential MA models based on their functional forms and independent (predictor) variables (i.e., Fraser River temperature and flow conditions, river entrance date, and annual escapement discrepancies). Mathematical models are explicit about their assumptions about the system and can document the rationale behind management decisions and thereby aid in tracking performance. To compare how well each model would have performed if it had been used in the past, I calculated a variety of performance measures (e.g., mean raw error, mean absolute error, root mean square error, mean small sample Akaike information criterion (AIC_c), and mean adjusted R^2) that compared forecasted in-river loss with actual in-river loss.

Alternative Forecasting Techniques

To use all of the information contained in various candidate models, it may be valuable to combine models to make a single, potentially more precise and less biased prediction. Thus, in addition to doing retrospective analyses of individual management adjustment models, I also explored the viability of applying three alternative techniques for combining those models used for Fraser River sockeye salmon MA forecasting: (1) combining them via a weighting scheme based on model fits, (2) combining them using performance-based optimization of model weights, and (3) combining models via switching rules that use one model rather than another based on the value of some independent variable. While use of model-combination techniques is expanding, the technique is relatively new, with variable usage and terminology in different disciplines.

For instance, use of model averaging based on an information criterion such as the small-sample Akaike Information Criterion (AIC_c) is expanding, and it has successfully improved model performance in many of its applications. Based on its performance to date, Link and Barker (2006), suggest increased usage and evaluation of model averaging in ecological sciences. Thus far, model averaging has been proposed as a means of setting rebuilding targets for New England groundfish stocks (Brodziak and Legault 2005), estimating vessel impacts on Mississippi River fisheries (Gutreuter et al. 2006) and making hydrological predictions (Duan et al. 2007). In addition, Adrian Raftery and his colleagues have applied Bayesian model averaging successfully to many fields, such as climatology and meteorology (Raftery et al. 1997, Raftery and Zheng 2003, Raftery et al. 2005). Despite this success and the expanding use model-averaging based on an information criterion, it has not been widely practiced and further evaluation has been recommended (Burnham and Anderson 2004). Therefore, my use of AIC_c weight model averaging for Fraser River sockeye salmon forecasts provides a potential opportunity to further evaluate model averaging and improve forecasts.

Unlike model averaging based on an information criterion, a second type of model averaging uses management-relevant performance measures such as mean absolute error, or other measures, to optimize the weight placed on the suite of model forecasts. This technique has been given many names, such as a weighted ensemble approach, weighted-average method, performance-weighted average and others, and has been used sporadically in weather predictions and economic forecasts (Eckel and Mass 2005, Woodcock and Engel 2005, Greybush et al. 2008). In my application of this technique, I will refer to it as using "optimized weights" to combine models.

The final model-combination technique I will analyze is the use of a switching rule to select which model to use in a given year. This technique is similar in concept to switching rules used in engineering (Narendra and Balakrishnan 1994, Narendra et al. 1995, Giovanini et al. 2006), which shift between multiple models to control manufacturing facilities. Outside of the engineering field, the use of switching rules is limited, but Haeseker et al. (2007) essentially used this method to develop what they called a "hybrid model" to forecast pre-season salmon abundance that switches between one forecasting method and another, depending on certain conditions. However, the term “hybrid model” is ambiguous; it could also simply be a single model with components drawn from the suite of available models. A more specific term such as switching-rule modeling, or a switching model is more appropriate. Given the paucity of previous ecological studies using a switching model, my exploratory analysis should help guide further pursuit of a technique to select between models to fit changing ecological conditions.

In summary, this analysis will examine the efficacy of a suite of six management adjustment models and three model-combination techniques to provide a framework for both current and continuing evaluation of alternative MA models, to stimulate identification of explicit fisheries objectives and appropriate indicators, and to improve achievement of objectives for Fraser River sockeye salmon.

Methods

Data

Fisheries and Oceans Canada (DFO) provided historical spawning escapement estimates for sockeye salmon (DFO stock assessment, T. Cone, Annacis Island, BC), and the Pacific Salmon Commission (PSC) provided sockeye salmon abundance estimates at Mission and estimates of sockeye salmon catch upriver of Mission. Spawning ground abundance estimates were obtained through a variety of observation techniques, whereas Mission abundance and run-timing estimates were obtained using hydroacoustic sonar (Xie and Hsieh 1989, Xie 2000). Fraser River temperatures were collected as part of the Fraser River Environmental Watch Program (Patterson et al. 2007a), and Fraser River flows were measured by Environment Canada’s Water Survey of Canada (http://scitech.pyr.ec.gc.ca/waterweb/). Temperature measurements were taken at Qualark, B.C. and flow measurements were from Hope, B.C. (Fig. 1-1).

Management Adjustment Models

For estimating natural mortality of upstream migrating adults, I used the "difference between estimates" (DBEs), which is the difference between estimates of upriver spawning escapement abundance (*SE*) and lower river potential spawning escapement abundance estimates (*PSE*) (Table 1-1). The latter, potential spawning escapement, accounts for the lower river escapement as well as upriver First Nations and recreational catches (Table 1-1). This proxy was necessary because scientists currently lack a direct measure for the magnitude of mortality for upstream migrating adult Fraser River sockeye salmon (Patterson et al. 2007b). More specifically, the DBE response variable is specified as the natural log of the quantity *SE* divided by *PSE*, $\ln(SE/PSE)$ (Hague and Patterson 2007). The reasons for a log-transformation are: (1) to meet assumptions of homoscedasticity in residuals from the fitted models (Zar 1996), and (2) to constrain predictions of SE/PSE within a positive range (Macdonald et al. 2009, in review).

This study evaluated models with four different predictor variables for forecasting adult abundance of Fraser River sockeye salmon: (1) Fraser River temperature (*T*) in degrees Celsius measured at Qualark, British Columbia, (2) Fraser River flow (*Q*) in cubic meters per second measured at Hope, British Columbia, (3) migration timing (D_{50}) e.g., river entry date, and (4) the observed historical average DBEs (*H*) (Table 1-2; Macdonald et al. 2009, in review). Six different MA models resulted (Eq. 1 – 6 in Table 1-2). Models 1-3 use either Fraser River temperature, Fraser River discharge, or both, whereas model 4 fits to historical DBEs using historical Hells Gate 50% median dates (i.e., the date at which 50% of the run has migrated past Hells Gate) (Eq. 4). Model 5 forecasts future DBEs using the average DBEs from the past. These models were all compared to each other and to the results of using no management adjustment (model 6). Run-specific parameters were estimated for each of these six candidate management adjustment models by fitting historical DBEs (ln(*SE*/*PSE*)) data to historical, environmental, or run-timing conditions using the equations in Table 1-2.

Retrospective Analysis

Models were initially fit to data on annual environmental variables and historical DBEs (ln(*SE*/*PSE*)) from 1977 – 1994. Retrospective predictions were then made for 1995 – 2007. For example, *a* and *b* parameters for a given model were initially estimated using data from 1977 -1994 and the resulting model was then used to forecast the DBE in 1995. In the next iteration, the observed 1995 data on annual environmental variables and DBEs were added to the time series, model parameters were re-fit, and the 1996 DBE was forecasted. These iterations were repeated for all remaining years of available data and for all run-timing groups. Models were fit using the linear modeling function in the statistical software package R (http://cran.r-project.org/). Note that because of limited data for the Late run-timing group, the temperature-plus-discharge model needed to be initialized from 1977 - 1997 and evaluated from 1998 – 2007 in order to have more initial data points than regression parameters. In addition, again because of data limitations for this timing group, the mean small-sample Akaike information criterion performance measure was averaged from 2000 - 2007 for the Late run-timing group temperature-plus-discharge model and 1998 - 2007 for the remaining models for this timing group.

Model performance measures. -- Fisheries management objectives can vary across fisheries and even over time within a fishery, depending on relative weighting placed on spawning vs. harvest goals, short-term vs. long-term plans, and acceptable characteristics of forecasting error, among other factors. Depending on the nature of such objectives, different measures will be better suited to evaluate model performance. I used five different performance measures to assess the suite of MA models listed above: (1) mean raw error (MRE), (2) mean absolute error (MAE), (3) root mean square error (RMSE), (4) mean small-sample size Akaike information criterion (AIC_c), and (5) mean adjusted R^2 (R^2). These commonly used measures were selected to provide an assessment of model bias, precision, and overall fit (Willmott 1982, Abraham and Ledolter 1983, Chatfield 2001, Burnham and Anderson 2002, Willmott and Matsuura 2005).

To facilitate interpretation of results, I converted model error, the difference between the predicted and observed values of ln(*SE*/*PSE*) based on equations 1-6, to "raw error" (*RE*) measured on a linear scale using:

(7) $$RE_{n,i} = \exp(\ln(SE/PSE)_{fore,n,i}) - \exp(\ln(SE/PSE)_{obs,n}),$$

where $RE_{n,i}$ is the raw error in year *n* of model *i*, $\ln(SE/PSE)_{fore,n,i}$ is the *forecasted* DBE in year *n*, as forecasted by model *i*, and $\ln(SE/PSE)_{obs,n}$ is the *observed* ln(*SE*/*PSE*) in year *n* (Table 1-1). By converting to the linear scale, a positive error of a given magnitude has the same value relative to the observed in-river loss as a negative error of the same magnitude (Table 1-1). Because in-river loss is measured by using the estimated ratio of spawners (*SE*) to number of fish entering the Fraser River (*PSE*), *RE* is a unitless, proportional measure of the extent to which the forecasted ratio of actual spawner abundance divided by Mission abundance represents the actual ratio realized at the end of the season; the larger the ratio, the smaller the in-river loss, assuming negligible estimation error.

Our measures of forecasting error require some explanation. For example, a *SE*/*PSE* of 1 indicates all fish estimated as potential spawners at Mission were later observed upstream on spawning grounds, whereas a *SE*/*PSE* of 0.5 indicates 50% of those potential spawners were estimated on those grounds. Therefore, a forecasted *SE*/*PSE* of 0.925 would predict that 92.5% of potential spawners at Mission would reach the spawning grounds (a predicted in-river loss of 7.5%). If the observed *SE*/*PSE* was actually 0.875, an in-river loss of 12.5% of the fish, then the difference between forecasted and observed ratios of *SE*/*PSE* results in a positive raw error of 0.05 (equation 7) (an underestimate of the in-river loss), which indicates that spawning objectives would not have been met (Table 1-1).

Because raw error (*RE*) is estimated from forecasted minus actual (observed) values of the exponentiated terms in Eq. 7, positive *RE*s represent forecasts of SE/PSE in the left-hand term of Eq. 7 that are closer to 1.0 than the true SE/PSE (right-hand term of Eq. 7) (Table 1-1). This situation would result in underestimation of management adjustments (i.e., too few additional fish being allowed to escape upriver), which would in turn produce fewer than the target number of spawners and greater allocation of catch than available to meet the spawning target (Table 1-1). In contrast, negative raw error values (*RE*) represent forecasts of SE/PSE that are further from 1.0 than the observed SE/PSE, resulting in management adjustments that would produce a number of spawners above the target and therefore a smaller harvest than achieving the spawning objective would have given (Table 1-1).

The MRE is the average bias for each model:

$$\textbf{(8)}\ MRE_i = \frac{\sum_{n=1995}^{N} RE_{n,i}}{N},$$

where MRE_i is the mean raw error for MA model i across all evaluated years (N), where i corresponds to models 1-6 in Table 1-2.

An unbiased model, with an equal magnitude of positive and negative raw errors (*RE*), results in a MRE = 0, but provides no indication of precision of forecasts. Therefore, MAE (Eq. 9) and RMSE (Eq. 10) were also calculated to assess the average magnitude of MA model residuals. The MAE is the average absolute magnitude of MA model error, regardless of sign:

$$\textbf{(9)}\ MAE_i = \frac{\sum_{n=1995}^{N} \left| RE_{n,i} \right|}{N}$$

The RMSE weights large errors more heavily, such that the model with the smallest RMSE results in the lowest variance in residuals:

(10) $$RMSE_i = \sqrt{\frac{\sum_{n=1995}^{N} \left(RE_{n,i}\right)^2}{N}}$$

Finally, I calculated two measures of goodness of fit to assess how well models fit observed data. Adjusted R^2 is the proportion of variability in ln(SE/PSE) explained by the MA model, while AIC_c uses model likelihood and number of model parameters to score degree of belief in the models relative to one another, irrespective of a "true model", and incorporates the principle of parsimony (Burnham and Anderson 2002). Because models were refit for each year of the retrospective analysis, a mean adjusted R^2 and a mean AIC_c across years are used for retrospective evaluation:

(11) $$R^2{}_i = \frac{\sum_{n=1995}^{N} R^2{}_{n,i}}{N}$$

(12) $$AIC_{c\,i} = \frac{\sum_{n=1995}^{N} AIC_{c\,n,i}}{N}$$

In addition to AIC_c, following standard AIC reporting procedure (Burnham and Anderson 2002), I report maximum log likelihood, number of parameters (K), delta AIC_c (Δ AIC_c), and AIC_c weight for each model.

In order to give these performance measures some context, the following is a discussion of the treatment of error as a measure of retrospective management performance. The performance measures, MRE, MAE, and RMSE, communicate how much a spawning escapement target would have been missed if a given management-adjustment model had been applied in past years. While treating error in this way places forecast error in the context of management, there are some important caveats to consider. One is that forecasted spawning escapements are compared to historically observed escapements rather than to spawning escapement targets set by the management agency. The reason is that the spawning escapement targets are updated during the fishing season. In this analysis, I assumed that spawning escapement targets were perfectly met in the past so that I could treat the historically observed escapements as the historical spawning escapement targets. Based on this assumption, I treat the difference between a historically observed escapement and a forecasted spawning escapement, i.e., the difference that would have resulted from retrospective application of a MA forecast, as the difference between the actual and target spawning escapement. Such a treatment of forecast errors also assumes that outcome uncertainty, which is uncertainty in the degree to which management actions are achieved in practice, is independent of forecasts by management adjustment models.

Each measure of performance of a forecasting model reflects a different perspective on management objectives. The information contained in any individual performance measure could be used to evaluate a model's ability to achieve one or more possible management objectives. Mean raw error communicates the average magnitude and direction by which spawning escapement targets would have been missed if a given model had been applied retrospectively. In contrast, mean absolute error quantifies the average magnitude by which escapement targets would have been missed, regardless of direction. RMSE, like MAE, is insensitive to whether error is positive or negative. In addition, RMSE weights large errors more heavily than smaller errors, potentially corresponding to increased stakeholder concerns associated with errors beyond some threshold level. Previous studies evaluated the performance of sockeye, chum (*O. keta*), and pink (*O. gorbuscha*) salmon preseason abundance forecasting models using these performance measures (Wood et al. 1997, Haeseker et al. 2005, Cass et al. 2006, Haeseker et al. 2008).

In addition to reporting the actual value of performance measures, a model rank was assigned to each MA model for each run-timing group and each performance measure, where 1 = "best" and 6 = "worst" model. For MRE, MAE, and RMSE, the best model was the one that had a performance measure closest to zero, while for the R^2 performance measure, the largest value was best, and for the AIC_c performance measure, the best model produced the smallest AIC_c value. In addition to determining individual ranks, to rank relative overall model performance, I averaged each MA model's rank across the ranks for each of the five performance measures in each run-timing group (MRE, MAE, RMSE, AIC_c, and R^2). For a given suite of run-specific MA models, I assigned overall model rank to each model using:

$$\textbf{(13)}\ rank_i = \frac{\sum_{j=1}^{J} rank_{i,j}}{J}$$

where $rank_i$ is the mean rank for model i, and $rank_{i,j}$ is the rank for model i for performance measure j, and $J = 5$.

Jack-knife.--A criticism of retrospective analysis is its use of historical information that may not represent future conditions because variability seen in the past may not reflect the range that may occur in the future. Such forecasts of future conditions are not possible, but I conducted a jack-knife analysis (Shao and Dongsheng 1995) to determine the sensitivity of model rankings and performance to removal of each year's forecast from the time series and to assess robustness of the retrospective ranking procedure to interannual variability. Single years of the 13-year retrospective evaluation period were sequentially removed and performance measures were re-estimated, eventually producing 13 replicates of model ranking. To assess the sensitivity of model rank to removal of an individual year's data, I compared the top-ranked model for each performance measure from the retrospective analysis to the top-ranked model for each performance measure from each jack-knife replicate, tracking the number of jack-knife replicates that selected a different top-ranked model.

Alternative Forecasting Techniques

AIC weights.—One of the options for combining models is to use model averaging based on information theoretic criteria (Burnham and Anderson 2004, Brodziak and Legault 2005, Gutreuter et al. 2006). I weighted annual forecasts produced by each model by the retrospective annual AIC_c weights (Eq. 14) to produce a single combined forecast.

(14) $$\ln\left(\frac{SE}{PSE}\right)_n = \sum_{i=1}^{6}\left[W_{n,i} \bullet \ln\left(\frac{SE}{PSE}\right)_{n,i}\right]$$

where $W_{n,i}$ is the AIC_c weight (between 0 and 1) in year n for model i, $\sum_{i=1}^{6} W_{n,i} = 1$, and $\ln(SE/PSE)_{n,i}$ is the forecasted value in year n from model i such that the weighting can vary from year to year. These retrospective annual AIC_c weights are based on the yearly estimates of AIC_c values that were used above in Eq. 12 to produce the AIC_c performance measure.

Optimized weights.—I also calculated three separate forecasts of in-river loss generated by an optimized-weight approach to minimize the three error-based performance measures (MRE, MAE, and RMSE); Eq. 15.

$$\textbf{(15)}\quad \ln\left(\frac{SE}{PSE}\right)_n = \sum_{i=1}^{5}\left[OW_{n,i} \bullet \ln\left(\frac{SE}{PSE}\right)_{n,i}\right]$$

where $OW_{n,i}$ is the optimized weight for year *n* and model *i*, $\sum_{i=1}^{5} OW_{n,i} = 1$, and $\ln(SE/PSE)_{n,i}$ is the forecasted value from year *n* and model *i*. Unlike the retrospective evaluation described above, in which each model forecast was evaluated with five performance measures, each optimized model forecast here was produced and evaluated using only a single performance measure. Specifically, only MRE was used to evaluate the MRE-optimized model, only MAE to evaluate the MAE model, and only RMSE for the RMSE model. As with the retrospective evaluation, I repeated this process iteratively for each year of the retrospective evaluation using the information available at that time. For example, the 2001 MRE-optimized forecast is based on the optimal set of weights on each model that, when combined with equation 15, minimize the mean raw error of the combined model forecasts from 1995-2000. I found the optimal set of weights, $OW_{n,i}$, by using Microsoft Excel's SOLVER. If a management adjustment was not applied, it would always predict zero in-river loss and would not affect the optimized forecast despite its weighting; therefore, not using a management adjustment was not included in the optimized model weighting.

The AIC_c weight and optimized-weight models were evaluated using three of the five performance measures, MRE, MAE, and RMSE. For each performance measure, the performances of these models were ranked against each other, as well as against the six models for each run-timing group from the retrospective analysis. For example, the MRE-optimized version of the optimized weight model was ranked against the single-AIC_c weighted model and the six independent models using just the MRE performance measure. This comparison was repeated for the MAE- and RMSE-performance measures using the MAE- and RMSE-optimized model forecasts. Here, rankings range from 1 (best) to 8 (worst) for each performance measure.

Switching rule.—A third option for an alternative approach to model development is to switch from one model to another based upon predicted conditions in the forecasted year. In order to switch between the set of available models from year to year in a strategic way, I sought to develop switching rules to define conditions that correspond to selecting a particular model.

For each set of observed environmental conditions, I plotted the model with the smallest *RE* to identify sets of those conditions that were dominated by a single model. The conditions used in this analysis are the same as those used in forecasting: Fraser River temperature, Fraser River discharge, and stock specific run-timing. Unlike the retrospective evaluation, which produced a version of each MA model for each year, I fit a single version of each model to the full time series (1977-2007) to produce the yearly forecast. Therefore, results of this section reflect how models would have performed in the past if all of the information that is currently available also existed in 1977. This particular analysis produced a multi-dimensional space, defined by historically observed Fraser River sockeye salmon migration conditions, populated by points corresponding to the best-performing model in each year.

Results

Retrospective Model Performance

Although there is some consistency in which models rank the highest (i.e., some perform well in all run-timing groups and for the majority of performance measures), ranks of most models varied as a function of run-timing group and the performance measure considered. Interannual variability in retrospective forecasts of difference between estimates (DBEs) by top-ranked management adjustment (MA) models differs from the observed DBEs for each sockeye salmon run-timing group (Fig. 1-2). For the Early Stuart and Summer run-timing groups, the historic (**H**) model was less biased relative to the observed DBE (as reflected by MRE) than the other models (Fig. 1-3), but did a poor job of tracking interannual variability in observed DBEs (Fig. 1-2). In contrast, the environmental models (temperature (**T**) model, discharge (**Q**) model, and temperature-plus-discharge (**T+Q**) model) displayed a temporal variance structure similar to the observed data, but the mean raw error (MRE) results are positive (Fig. 1-3). This positive MRE means that the models are generally biased towards forecasting an MA that, if applied historically, would have resulted in positive raw error (i.e., underestimates of in-river loss, which result in escapements below spawning targets; refer back to Table 1-1). The only exceptions are the Early Stuart and Early Summer **H** models, and the Late run **H** and run-timing (R) models, all of which have small negative MREs and therefore are slightly biased towards overestimates of in-river loss (leading to exceeding spawning targets).

Based on the average rank of models calculated across ranks specific to each performance measure, no single model performed best across all run-timing groups (Fig. 1-4). However, one clear result is that failure to apply a management adjustment, the "No MA" (**NMA**) model, had the worst average rank in three of the four run-timing groups, and the second-worst rank in the other group. The **H** model achieved the best ranking for the Early Stuart run, the **H** and the **T+Q** MA models tied for highest rank for the Early Summer run, the **T** and the **T+Q** models were tied for best for the Summer run, and the **R** model was best for the Late run (Fig. 1-4).

Separating average results from Fig. 1-4 by performance measure as well as model shows that model rank not only varied across run-timing group, but also across measures used to assess model performance (e.g., MRE, MAE, etc., Fig. 1-5). In some cases, the best performing model was consistent across performance measures. The **R** model in the Late run-timing group ranked best for all five performance measures (Fig. 1-5D). Similarly, the Early Stuart **H** model ranked first for four performance measures (MRE, MAE, RMSE, AIC_c) and third for R^2 (Fig. 1-5A). As was seen previously in Figure 1-4, the **NMA** model ranked poorly in all run-timing groups; it ranks last for almost all performance measures in the Early Stuart and Early Summer run-timing groups and generally performs poorly in the Summer and Late run analyses as well. However, although the **NMA** model performed poorly, it did not rank lowest for any of the Summer run performance measures; the **R** and **Q** models for the Summer run each had the lowest rank for one or more of the five performance measures (Fig. 1-5C). Disagreement among performance measures about ranks of models can also arise, as demonstrated by the MRE and MAE performances for the Summer run-timing group. In this example, the **H** model performs best for MRE, and the **T+Q** model performs second best based on MRE, whereas for MAE and RMSE, the **T+Q** model performs better than the **H** model. These results reflect the importance of carefully articulating management objectives to identify performance measures that best reflect them.

A model's rank for each individual performance measure provides a more detailed view of performance. For the Early Stuart run-timing group, the **H** model ranked best in terms of having the smallest average bias (MRE), average absolute error (MAE), average RMSE, and average AIC_c score, while the **T** model ranked second for all five performance measures (Fig. 1-5A). The **T+Q** model ranked first based on R^2, despite its relatively poor performance for the other measures. For the Early Summer run (Fig. 1-5B), the **H** model best explained the observed variance (R^2 and AIC_c), but the **T+Q** model ranked best for MAE and RMSE, and the **Q** model ranked first for the MRE measure despite an otherwise poor performance. For the Summer run-timing group (Fig. 1-5C), the **T+Q** model had the smallest MAE and the best RMSE rank. However, likely because of the **T+Q** model's additional parameters relative to the **T** model, the **T** model performed best for adjusted R^2 and AIC_c.

An examination of actual values of each performance measure (instead of ranks) provides additional insight into differences among models (Fig. 1-3). In many instances, the differences between model ranks was due to only minor differences in the actual value of the performance measures (Fig. 1-3). For example, in the Early Stuart and Early Summer run-timing groups, differences among the top several models in the MAE and

RMSE values were quite small (Fig. 1-3A, B). This is particularly true of the Early Stuart MAE scores, where the best-ranked model had a MAE of 0.21 and the fifth-ranked model had a MAE of 0.25. However, a caveat to this point for the Early Summer group is that the MRE of the **T+Q** model error was 0.04 and the **Q** model was 0.02, which is a small absolute difference, but a large percentage difference. Thus, both rank and numerical error are informative in communicating model performance.

The R^2 and AIC_c results also contribute to understanding model performances. There was considerable variation in the adjusted R^2 values among run-timing groups, with the **R** model explaining 72% of the observed information in the Late run-timing group (Fig. 1-3D), while the top-ranked model for the Early Summer run (the **H** model) only explained 22% (Fig. 1-3B). The model with the largest R^2 value often ranked poorly for the MRE, MAE, and RMSE performance measures. For example, the Early Stuart run **T+Q** model ranked first based on adjusted R^2 but ranked third for MRE or fifth for MAE and RMSE (Fig. 1-5A).

Based upon AIC_c differences (ΔAIC_c) (Fig. 1-6), the **H** model was best for the Early Stuart and Early Summer runs, while the **T** and **R** models were best for the Summer and Late run-timing groups, respectively. The only other model with substantial empirical support, i.e. with a ΔAIC_c less than 2, was the Early Stuart **T** model. However, while ΔAIC_c is informative, there were situations where models with a large ΔAIC_c performed quite well, based on other performance measures, such as the Early Summer and Summer run-timing groups' **T+Q** models in particular (Table 1-3 for complete AIC_c results).

Finally, model performance varied considerably from year to year as can be seen from the frequency (number of years) that a model performed best in terms of yearly raw error (RE from Eq. 7) (Fig. 1-7). Using the Early Stuart run-timing group as an example, although the **H** model ranked best (average rank = 1.4), it produced the smallest raw error in only two of the 13 years of the retrospective evaluation. The **T+Q** model, which had average rank of 3.4, had the smallest raw error in four of 13 years, the most years of any model for Early Stuart. While the largest difference between average model rank across the five performance measures and frequency of best performance occurred for the Early Stuart run, similar divergences occurred for the yearly model performance in other run-timing groups. Using the yearly model performance to examine whether there is any correspondence between environmental conditions and model performance may provide additional useful information. I examined this in the switching rule analysis later.

Jack-knife

The jack-knife analysis of this retrospective evaluation indicated that results presented here are quite robust to year-to-year variation in model forecasts for three of the four run-timing groups (Table 1-4; Appendix 2). In the Early Summer, Summer, and Late run-timing groups, only a few, if any, of the jack-knife replicates caused a different model to rank better than the top-ranking model that was derived from the full retrospective evaluation. Ranks of models of the Early Stuart run-timing group were the most sensitive to the jack-knife analysis, with the MAE and RMSE performance measures indicating that an alternative model performed best in 46% and 54% of the replicates, respectively. This result is likely due to the similarity in model performance among the models in both the MAE and RMSE performance measures for this group (Fig. 1-3A).

Alternative Forecasting Techniques

Based on their aggregate performance using the MRE, MAE, and RMSE performance measures, i.e., excluding mean adjusted R^2 and mean AIC_c, both the AIC-weight and optimized-weight alternative forecasting techniques performed well for the Early Summer and the Late run-timing groups, where they outperformed 5 of the 6 standard models (Fig. 1-8). In contrast, for the Early Stuart run, the optimized model weights and model averaging techniques ranked 3rd and 4th, respectively, out of 8 models. For the Summer run-timing group, the alternative model techniques performed poorly, only outperforming the two worst models. There was little difference between the rankings of the two alternative modeling techniques across run-timing groups, but the optimized model weight approach outperformed the AIC_c weight approach for all but the Late run-timing group.

The only situation where a model-combination technique could be considered superior to the best standard forecasting technique occurred for the Late run-timing group. The AIC_c weighting approach and the run-timing model both tied for best (Fig. 1-8), but the run-timing model ranked 1st for MRE, 2nd for MAE, and 3rd for RMSE, while the model averaging approach ranked 3rd for MRE, 1st for MAE, and 2nd for RMSE (calculated from Appendix 1). This is another example of trade-offs among performance measures. In this situation, an ordering of the importance of these different performance measures, or a means of comparing the size of the numerical error from one performance measure to another, is necessary to identify a preferred model.

Switching rules.--Examination of multi-dimensional plots of model performance for the suite of six models as a function of environmental conditions did not yield any strong clustering patterns in terms of a model that performs best in terms of *RE* under a particular set of environmental conditions (Fig 1-9). However, there are some points that could be explored further in the future (Appendix 3). For example, in the Early Stuart run-timing group, the **Q** model tended to outperform other models in years with low temperature and high discharge, and the **NMA** model only performed best in years with low discharge (less than 5,000 cubic meters per second), (Fig. 1-9A). For the Summer run-timing group, the **T** model only performed best in years with low discharge (less than 3,000 cubic meters per second) (Fig. 1-9C). Outside of these examples, environmental conditions and run-timing do not appear to be clearly correlated with any model producing the best forecast under those environmental conditions.

Discussion

The retrospective analysis presented here provides a framework for comparing current and future management adjustment (MA) models. It will also be easy to evaluate new models or re-evaluate existing models as additional years of data become available. This analysis also shows the importance of developing clear management objectives and their accompanying performance measures to select MA models; model rankings can vary considerably, depending upon the run-timing group and performance measure selected. When combined with clear management objectives, my methods of model selection can help managers make management-adjustment decisions that will increase the chance of more closely achieving management objectives.

One key finding from my study is the strong evidence that MA forecasts from some combination of environmental or biological data are preferable to applying no MA to the harvest; using no management adjustment produced the poorest results in almost all cases. The historic model performed best based upon the MRE performance measure in half of the run-timing groups, which indicates that this model produced the least bias, on average, except in the case of the Summer and Late run-timing groups. This is likely due to the nature of the historic model; as long as the observed DBE follows some general trend over time and is not too variable from year-to-year, it follows logically that a model based on the past DBE trend would have relatively little bias. However, except for the Early Stuart run-timing group, the environmentally based models (temperature, discharge, temperature-plus-discharge, and run-timing) often performed best for the MAE and RMSE performance measures, i.e., those that reflect magnitude of deviations, not just overall bias. Combining ranks across individual performance measures into an aggregate rank resulted in one or two highly ranked models for each run-timing group. Generally those best-ranked models for the Early Stuart, Early Summer, and Summer run-timing groups were two of the following three: temperature, temperature-plus-discharge, or historic models, whereas the run-timing model was best ranked for the Late run-timing group.

Managers also need to consider how big a difference in performance is needed to decide that one model is better than another because the difference in performance of the top two models in a given year was often quite small (Appendix 1). This observation suggests that using average ranks and average values of performance measures (Fig. 1-3 to 1-6) are likely to be more useful than basing model choice on the number of years that a model had the smallest raw error (Fig. 1-7). Even if managers use the former performance measures, they still need to consider what constitutes a meaningful difference. An MRE difference of 5% is perhaps too small to be concerned with, but what about 10%, 20% or 40%? In addition, is a difference of 20% for MRE more important than a difference of 20% for the MAE performance measure? In the Early Stuart and Early Summer run-timing groups, differences among top models for the MAE and RMSE performance measures were quite small. For example, the 5th ranked model's MAE for the Early Stuart run was only 19% greater than the best ranked model's MAE and the 2nd ranked model's MAE was only 4% greater than that of the best model.

Because of the dependence of model rank on the performance measure used, I support the use of multiple performance measures in model selection or at least the practice of ensuring that the performance measures used appropriately represent management objectives. Many studies use only one or two measures to rank model performance (e.g., Willmott 1982, Willmott and Matsuura 2005); a practice that only captures certain characteristics of the model performance. Given the sensitivity of model rank to the choice of performance measure, managers should be aware that models selected on the basis of a single performance measure such as MRE or MAE may result in larger errors or failure to meet objectives that are reflected by other performance measures. However, when a performance measure contains multiple types of information, such as the RMSE, which reflects both bias and precision, it becomes more difficult to interpret (Willmott and Matsuura 2005). Therefore, using the root mean squared error alone could lead to ambiguous interpretations that are more easily avoided by a more diverse set of performance measures. In addition, making decisions using only the MRE measure of bias would assume that managers only aim to achieve small average bias over the long term, but this would ignore the impact of uncommon but very large positive or negative forecasting errors, which managers also likely seek to avoid. Using both MRE and RMSE, however, could capture both aspects of these management objectives.

Many studies in ecology select models from a large set based solely on R^2 or AIC performance. While these studies may select biologically relevant models that fit historical data well, they may not perform well in terms of management objectives, as suggested by the discrepancy between model performances for the R^2 or AIC_c performance measures and the MRE, MAE, and RMSE measures. In nearly all cases, the top-ranked mean AIC_c model and the top-ranked mean adjusted R^2 model were not the top-ranked model for the MRE, MAE, or RMSE performance measures. These results in some ways are analogous to those of Adkison (2009) who found in a simulation study that models selected based on a decision-analytic approach outperformed models selected based on a maximum-likelihood approach. In addition, solely considering R^2 or AIC performance can be particularly problematic if there are asymmetric costs associated with exceeding or falling below an objective (Walters and Martell 2004; Chapter 2 of this thesis).

While retrospective analysis has been criticized for its use of historical information rather than future forecasts of performance, a jack-knife analysis showed that model performance based on my retrospective analysis was relatively insensitive to variability in year-to-year performance for three of four run-timing groups. The average performance was not heavily influenced by extreme years, as was shown by the few cases that produced a different top-ranked model.

The model-combination techniques were of variable benefit to Fraser River MA forecasts. Model averaging using AIC_c weighting did not out-perform the predictions of the "best" model. Instead, model averaging tended to provide little improvement in most cases because the error from this technique was midway between that of the best and worst models. However, for the Late run-timing group, the AIC_c weight model averaging ranked as well as the run-timing model. In general terms, relative to the best individual model, model averaging only improves forecasts when the error for at least some of the combined models is in opposing directions. That is, combining positive and negative forecasts will bring the average closer to zero. Because most of the models in my analysis produce overestimates of in-river loss, model averaging did not outperform the best individual models, but instead produced errors that were still overestimates and were the average of the individual model errors. There are some advantages to model averaging, though. It minimizes the influence of any individual forecast, and may eliminate rare, large errors associated with selecting a single model by averaging that large error with other forecasts, which would reduce the RMSE (Raftery and Zheng 2003). An additional advantage of the model averaging approach relative to the optimized weighting approach was that the fluctuations in models weights over time were smaller, indicating that the AIC_c weightings are more robust to annual variability.

The optimized-model-weight technique also ranked in the middle of the group of models in terms of average model rank. This technique performed slightly better than AIC_c weight model averaging for three of the four run-timing groups. However, an important caveat to selecting model forecasts based on an optimized weight combination is that the weights for individual models varied greatly depending on the type of error being minimized (MRE, MAE, or RMSE). Therefore, this technique would be most useful only if managers decided that a single performance measure captures the majority of the management objectives. Otherwise, because the optimized model weighting technique only optimizes for one performance measure at a time, managers may find that selecting the optimized-model-weight technique meets some of their objectives while failing to meet others.

Recommendations

Given the range of results that I found for different situations, it is clear that managers of Fraser River sockeye salmon fisheries and Fraser River fisheries scientists will need to consider a variety of different factors when selecting the most appropriate MA model for forecasting escapement discrepancies and to improve management. For example:

1. What are the management objectives of the fisheries?
2. What performance measure(s) best represent(s) these objectives?
3. How do models rank for this performance measure (or set of performance measures)?
4. How important are the magnitudes of differences between the top ranked models for those performance measures?
5. What is the best trade-off between selecting a model that performs well for one performance measure (or set of performance measures) but not another?
6. How sensitive is model performance to the years used in the analysis?
7. Can additional modeling techniques or alternative models improve forecast performance?

Some of these questions have been addressed by this research (i.e., 3, 5, 6, 7), while some require further consideration (i.e., 1, 2, 4).

To elaborate upon this list, the first step in decision making is to clearly state management objectives so that (1) management actions are chosen based on objectives, (2) management performance can be evaluated against objectives, and (3) appropriate indicators can be calculated to show how well each objective is being met. Two objectives established by the Pacific Salmon Treaty and Canadian legislation with regard to Fraser River sockeye salmon are conservation through achieving spawning escapement targets, and achievement of catch allocation goals (Woodey 1987, Shepard and Argue 2005). Although these generally stated objectives are helpful, they are too general to evaluate quantitatively, i.e., they are not "operational" objectives.

More specific objectives and their corresponding performance indicators are necessary in order to choose the most appropriate model for estimating MAs for any given run-timing group in a given year. For instance, do managers prefer a model that has the lowest average bias in errors over the long term (in which equally large over- and underestimates will tend to cancel each other out to give a bias of near zero), or do they prefer a model that has a larger average long-term bias but smaller average annual deviations, regardless of sign? The first version of the objective stated above would be addressed by using MRE to compare models, whereas the second would be based on MAE. In addition, do managers prefer consistent moderate-sized forecast errors from year to year, or do they prefer mostly small forecast errors accompanied by the occasional large forecast error? We know that fisheries managers already consider various types of measures of management performance, but they need to be more clearly articulated to choose appropriate MA models.

To select performance measures and determine how large the differences in values of performance measures need to be to prefer one model over another, managers could either rank or weight performance measures. For the Summer run-timing group as an example, if a manager favored small bias (MRE) but was less concerned about absolute error (MAE) and accepted some years with large error (RMSE), the manager would select the historic model because of its small bias despite its large absolute error. Conversely, a manager who selected the Summer run temperature-plus-discharge model is implicitly showing a relative indifference to model bias (MRE) in favor of minimizing the absolute deviation (MAE) and limiting the size of the largest errors (RMSE).

When managers address the appropriate questions stated above, or otherwise clarify their management objectives in terms of performance measures, scientists can provide better information on which to base decisions on management of salmon populations. However, managers may find that even with refined management objectives, it is still difficult to identify a single "best" MA model for each run-timing group. Managers may find that the model rankings presented here do not conform to their specific management objectives and corresponding performance measure(s). For example, managers may want to select the appropriate model based upon one or more of the following, (1) a different performance measure or set of performance measures than examined here, (2) a weighted average of performance measures, (3) performance measures that weight the failure to meet spawning targets more heavily than exceeding spawning targets by the same amount, or vice versa, e.g., using an asymmetric loss function (Chapter 2 of this thesis), or (4) some alternative loss function.

Because it may be difficult to elucidate exact management objectives, particularly in terms of positive versus negative forecasting errors, another valuable extension of this evaluation of alternative forecasting models is a sensitivity analysis of the effect of utilizing asymmetric loss functions to compute the raw error associated with those forecasts (Chapter 2 of this thesis). For example, various interest groups may weight exceeding spawning objectives and falling below them differently. The retrospective evaluation approach used here can help determine whether changing the weight applied to directional biases influences the outcome in terms of model selection.

Further exploration of model-combination techniques could prove useful as well. For example, in some cases, removing weaker models from the pool, leaving only higher ranking models available for forecasting, may result in more favorable model-combination forecasts. However, because most of the models tend to underestimate in-river loss, this is unlikely to improve model-combination forecasts. Another possibility is to explore utilizing additional model-combination techniques such as those from the meteorological literature. For example, Eckel and Mass (2005) used a 2-week moving window and selected models that performed best based on observed climatic conditions over that 2-week period, which could be analogous to using something like a 10-year moving window to select models that performed best based on the Fraser River conditions in those 10-years. This technique may be valuable if in-river losses fluctuate with decadal or other periodic changes in weather patterns, Fraser River conditions, or migratory behavior of sockeye salmon.

Potential improvement could also come from examining models beyond the suite of models considered in this analysis. There is potentially a wide range of additional management adjustment models, with different model structures and/or predictor variables, which could explain some of the historical variation in past escapement discrepancies. Some examples of additional predictor variables may include: (1) days during migration that the water is above some run-specific temperature and discharge thresholds, (2) mean daily Mission abundance (because it is possible that greater abundance may cause crowding, slower migration, and increased energy usage, thereby increasing migration difficulty), (3) observed DBEs from earlier-timed groups to subsequently forecast later run-timing groups (e.g., Early Summer, Summer and Late), (4) migration speed which can be associated with higher en-route mortality (Naughton et al. 2005) and might be predictable using gross somatic energy (Hanson et al. 2008), and (5) temperature compared to the optimum determined by aerobic scope, which is a measure of the metabolic ability of salmon to handle difficult conditions during upstream migration (Farrell et al. 2008). One benefit of the retrospective evaluation approach is that as scientists or managers identify new modeling approaches, additional models can easily be evaluated using the same retrospective analysis framework presented here, fitting regressions to predictor variables, making retrospective forecasts, and using performance measures to evaluate those forecasts against management objectives.

Due to the sensitivity of the rank order of models to choice of performance measures, managers will have to carefully consider the set of performance measures than best reflect their goals for the fishery. Ultimately, in conjunction with clearly specified management objectives and the corresponding development of their performance indicators, the results of this study can help provide a standardized process for selecting management adjustment models, which should increase the probability of achieving spawning escapement targets while balancing the trade-offs between allocation and conservation.

Reference List

Abraham, B. and J. Ledolter. 1983. Statistical Methods for Forecasting. John Wiley & Sons, New York.

Adkison, M. D. 2009. Drawbacks of complex models in frequentist and Bayesian approaches to natural-resource management. Ecological Applications **19**:198-205.

Brodziak, J. and C. M. Legault. 2005. Model averaging to estimate rebuilding targets for overfished stocks. Canadian Journal of Fisheries and Aquatic Sciences **62**:544-562.

Burnham, K. P. and D. R. Anderson. 2002. Model Selection and Multimodel Inference. Second edition. Springer-Verlag, New York.

Burnham, K. P. and D. R. Anderson. 2004. Multimodel inference - understanding AIC and BIC in model selection. Sociological Methods & Research **33**:261-304.

Cass, A., M. Folkes, C. Parken, and C. Wood. 2006. Pre-season run size forecasts for Fraser River sockeye for 2006.

Chatfield, C. 2001. Time-series forecasting. CRC Press LLC, Boca Raton.

Cooke, S. J., S. G. Hinch, G. T. Crossin, D. A. Patterson, K. K. English, M. C. Healey, J. S. Macdonald, J. M. Shrimpton, J. L. Young, A. Lister, G. Van Der Kraak, and A. P. Farrell. 2008. Physiological correlates of coastal arrival and river entry timing in late summer Fraser River sockeye salmon (*Oncorhynchus nerka*). Behavioral Ecology **19**:747-758.

Cooke, S. J., S. G. Hinch, A. P. Farrell, M. F. Lapointe, S. R. M. Jones, J. S. Macdonald, D. A. Patterson, M. C. Healey, and G. Van Der Kraak. 2004. Abnormal migration timing and high en route mortality of sockeye salmon in the Fraser River, British Columbia. Fisheries **29**:22-33.

Crossin, G. T., S. G. Hinch, S. J. Cooke, D. W. Welch, S. D. Batten, D. A. Patterson, G. Van Der Kraak, J. M. Shrimpton, and A. P. Farrell. 2007. Behaviour and physiology of sockeye salmon homing through coastal waters to a natal river. Marine Biology **152**:905-918.

Crossin, G. T., S. G. Hinch, S. J. Cooke, D. W. Welch, D. A. Patterson, S. R. M. Jones, A. G. Lotto, R. A. Leggatt, M. T. Mathes, J. M. Shrimpton, G. Van der Kraak, and A. P. Farrell. 2008. Exposure to high temperature influences the behaviour, physiology, and survival of sockeye salmon during spawning migration. Canadian Journal of Zoology-Revue Canadienne De Zoologie **86**:127-140.

Duan, Q. Y., N. K. Ajami, X. G. Gao, and S. Sorooshian. 2007. Multi-model ensemble hydrologic prediction using Bayesian model averaging. Advances in Water Resources **30**:1371-1386.

Eckel, F. A. and C. F. Mass. 2005. Aspects of effective mesoscale, short-range ensemble forecasting. Weather and Forecasting **20**:328-350.

English, K. K., W. R. Koski, C. Sliwinski, A. Blakley, A. Cass, and J. C. Woodey. 2005. Migration timing and river survival of late-run Fraser River sockeye salmon estimated using radiotelemetry techniques. Transactions of the American Fisheries Society **134**:1342-1365.

Farrell, A. P., S. G. Hinch, S. J. Cooke, D. A. Patterson, G. T. Crossin, M. Lapointe, and M. T. Mathes. 2008. Pacific Salmon in Hot Water: Applying Aerobic Scope

Models and Biotelemetry to Predict the Success of Spawning Migrations. Physiological and Biochemical Zoology **81**:697-708.

Gable, J. and S. Cox-Rogers. 1993. Stock identification of Fraser River sockeye salmon : methodology and management application. Pacific Salmon Commission Technical Report **No. 5**:36 p.

Giovanini, L., A. W. Ordys, and M. J. Grimble. 2006. Adaptive predictive control using multiple models, switching and tuning. International Journal of Control Automation and Systems **4**:669-681.

Greybush, S. J., S. E. Haupt, and G. S. Young. 2008. The Regime Dependence of Optimally Weighted Ensemble Model Consensus Forecasts of Surface Temperature. Weather and Forecasting **23**:1146-1161.

Gutreuter, S., J. M. Vallazza, and B. C. Knights. 2006. Persistent disturbance by commercial navigation alters the relative abundance of channel-dwelling fishes in a large river. Canadian Journal of Fisheries and Aquatic Sciences **63**:2418-2433.

Haeseker, S. L., B. Dorner, R. M. Peterman, and Z. M. Su. 2007. An improved sibling model for forecasting chum salmon and sockeye salmon abundance. North American Journal of Fisheries Management **27**:634-642.

Haeseker, S. L., R. A. Peterman, and Z. M. Su. 2008. Retrospective evaluation of preseason forecasting models for sockeye and chum salmon. North American Journal of Fisheries Management **28**:12-29.

Haeseker, S. L., R. M. Peterman, Z. M. Su, and C. C. Wood. 2005. Retrospective evaluation of preseason forecasting models for pink salmon. North American Journal of Fisheries Management **25**:897-918.

Hague, M. J. and D. A. Patterson. 2007. Quantifying the sensitivity of Fraser River sockeye salmon (*Oncorhynchus nerka*) management adjustment models to uncertainties in run timing, run shape and run profile. Canadian Technical Report of Fishieries and Aquatic Sciences **2776**:p.

Hanson, K. C., S. J. Cooke, S. G. Hinch, G. T. Crossin, D. A. Patterson, K. K. English, M. R. Donaldson, J. M. Shrimpton, G. Van der Kraak, and A. P. Farrell. 2008. Individual variation in migration speed of upriver-migrating sockeye salmon in the Fraser River in relation to their physiological and energetic status at marine approach. Physiological and Biochemical Zoology **81**:255-268.

Hanson, P. J., D. S. Vaughan, and S. Narayan. 2006. Forecasting annual harvests of Atlantic and Gulf Menhaden. North American Journal of Fisheries Management **26**:753-764.

Hinch, S. G. and J. Bratty. 2000. Effects of swim speed and activity pattern on success of adult sockeye salmon migration through an area of difficult passage. Transactions of the American Fisheries Society **129**:598-606.

Hinch, S. G., R. E. Diewert, T. J. Lissimore, A. M. J. Prince, M. C. Healey, and M. A. Henderson. 1996. Use of electromyogram telemetry to assess difficult passage areas for river-migrating adult sockeye salmon. Transactions of the American Fisheries Society **125**:253-260.

Hinch, S. G. and P. S. Rand. 1998. Swim speeds and energy use of upriver-migrating sockeye salmon (*Oncorhynchus nerka*): role of local environment and fish characteristics. Canadian Journal of Fisheries and Aquatic Sciences **55**:1821-1831.

Hinch, S. G., E. M. Standen, M. C. Healey, and A. P. Farrell. 2002. Swimming patterns and behaviour of upriver-migrating adult pink (*Oncorhynchus gorbuscha*) and sockeye (*O. nerka*) salmon as assessed by EMG telemetry in the Fraser River, British Columbia, Canada. Hydrobiologia **483**:147-160.

Holt, C. A. and R. M. Peterman. 2004. Long-term trends in age-specific recruitment of sockeye salmon (*Oncorhynchus nerka*) in a changing environment. Canadian Journal of Fisheries and Aquatic Sciences **61**:2455-2470.

Keefer, M. L., C. A. Peery, and M. J. Heinrich. 2008. Temperature-mediated en route migration mortality and travel rates of endangered Snake River sockeye salmon. Ecology of Freshwater Fish **17**:136-145.

Lapointe, M., S. J. Cooke, S. G. Hinch, A. P. Farrell, S. Jones, S. Macdonald, D. Patterson, M. C. Healey, and G. Van Der Kraak. 2003. Late-run sockeye salmon in the Fraser River, British Columbia, are experiencing early upstream migration and unusually high rates of mortality – what is going on? Proceedings of the 2003 Georgia Basin/Puget Sound Research Conference, Vancouver, B.C.

Lee, C. G., A. P. Farrell, A. Lotto, M. J. MacNutt, S. G. Hinch, and M. C. Healey. 2003. The effect of temperature on swimming performance and oxygen consumption in adult sockeye (*Oncorhynchus nerka*) and coho (*O. kisutch*) salmon stocks. Journal of Experimental Biology **206**:3239-+.

Link, W. A. and R. J. Barker. 2006. Model weights and the foundations of multimodel inference. Ecology **87**:2626-2635.

Macdonald, J. S. 2000. Mortality during the migration of Fraser River sockeye salmon (*Oncorhynchus nerka*) : A study of the effect of ocean and river environmental conditions in 1997. Canadain Technical Report of Fisheries and Aquatic Sciences **2315**:120 p.

Macdonald, J. S., M. G. G. Foreman, T. Farrell, I. V. Williams, J. grout, A. Cass, J. C. Woodey, H. Enzenhofer, W. C. Clarke, R. Houtman, E. M. Donaldson, and D. Barnes. 2000. The influence of extreme water temperatures on migrating Fraser River sockeye salmon (*Oncorhynchus nerka*) during the 1998 spawning season. Canadian Technical Report of Fisheries and Aquatic Sciences **2326**:117 p.

Macdonald, J. S., D. A. Patterson, M. J. Hague, and I. C. Guthrie. 2009. Improving the sustainability of sockeye salmon fisheries by modeling the influence of environmental factors on spawning migration success.

Narendra, K. S. and J. Balakrishnan. 1994. Improving transient-response of adaptive-control systems using mulitple models and switching. Ieee Transactions on Automatic Control **39**:1861-1866.

Narendra, K. S., J. Balakrishnan, and M. K. Ciliz. 1995. Adaptation and learning using multiple models, switching, and tuning. IEEE Control Systems Magazine **15**:37-51.

Naughton, G. P., C. C. Caudill, M. L. Keefer, T. C. Bjornn, L. C. Stuehrenberg, and C. A. Peery. 2005. Late-season mortality during migration of radio-tagged adult sockeye salmon (*Oncorhynchus nerka*) in the Columbia River. Canadian Journal of Fisheries and Aquatic Sciences **62**:30-47.

Patterson, D. A., J. S. Macdonald, K. M. Skibo, D. P. Barnes, I. Guthrie, and J. Hills. 2007a. Reconstructing the summer thermal history for the lower Fraser River, 1941 to 2006, and implications for adult sockeye salmon (*Oncorhynchus nerka*) spawning migration.

Patterson, D. A., K. M. Skibo, D. P. Barnes, J. A. Hills, and J. S. Macdonald. 2007b. The influence of water temperature on time to surface for adult sockeye salmon carcasses and the limitations in estimating salmon carcasses in the Fraser River, British Columbia. North American Journal of Fisheries Management **27**:878-884.

Peters, C. N., D. R. Marmorek, and R. B. Deriso. 2001. Application of decision analysis to evaluate recovery actions for threatened Snake River fall chinook salmon (*Oncorhynchus tshawytscha*). Canadian Journal of Fisheries and Aquatic Sciences **58**:2447-2458.

Raftery, A. E., T. Gneiting, F. Balabdaoui, and M. Polakowski. 2005. Using Bayesian model averaging to calibrate forecast ensembles. Monthly Weather Review **133**:1155-1174.

Raftery, A. E., D. Madigan, and J. A. Hoeting. 1997. Bayesian model averaging for linear regression models. Journal of the American Statistical Association **92**:179-191.

Raftery, A. E. and Y. Y. Zheng. 2003. Discussion: Performance of Bayesian model averaging. Journal of the American Statistical Association **98**:931-938.

Rand, P. S. and S. G. Hinch. 1998. Swim speeds and energy use of upriver-migrating sockeye salmon (*Oncorhynchus nerka*): simulating metabolic power and assessing risk of energy depletion. Canadian Journal of Fisheries and Aquatic Sciences **55**:1832-1841.

Rand, P. S., S. G. Hinch, J. Morrison, M. G. G. Foreman, M. J. MacNutt, J. S. Macdonald, M. C. Healey, A. P. Farrell, and D. A. Higgs. 2006. Effects of river discharge, temperature, and future climates on energetics and mortality of adult migrating Fraser River sockeye salmon. Transactions of the American Fisheries Society **135**:655-667.

Richter, A. and S. A. Kolmes. 2005. Maximum temperature limits for chinook, coho, and chum salmon, and steelhead trout in the Pacific Northwest. Reviews in Fisheries Science **13**:23-49.

Roos, J. F. 1991. Restoring Fraser River salmon. Pacific Salmon Commission, Vancouver, BC.

Shao, J. 1993. Linear-model Selection by Cross-validation. Journal of the American Statistical Association **88**:486-494.

Shao, J. and T. Dongsheng. 1995. The Jackknife and Bootstrap. Springer - Verlag, New York.

Shepard, M. P. and A. W. Argue. 2005. The 1985 Pacific Salmon Treaty: sharing conservation burdens and benefits. UBC Press, Vancouver.

Standen, E. M., S. G. Hinch, M. C. Healey, and A. P. Farrell. 2002. Energetic costs of migration through the Fraser River Canyon, British Columbia, in adult pink (*Oncorhynchus gorbuscha*) and sockeye (*Oncorhynchus nerka*) salmon as assessed by EMG telemetry. Canadian Journal of Fisheries and Aquatic Sciences **59**:1809-1818.

Walters, C. J. and S. Martell. 2004. Fisheries Ecology and Management. Princeton University Press, Princeton.

Willmott, C. J. 1982. Some Comments on the Evaluation of Model Performance. Bulletin of the American Meteorological Society **63**:1309-1313.

Willmott, C. J. and K. Matsuura. 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research **30**:79-82.

Wood, C. C., D. T. Rutherford, D. Peacock, S. Cox-Rogers, and L. Jantz. 1997. Assessment of recruitment forecasting methods for major sockeye and pink salmon stocks in northern British Columbia. Canadian Technical Report of Fisheries and Aquatic Sciences **2187**:85 p.

Woodcock, F. and C. Engel. 2005. Operational consensus forecasts. Weather and Forecasting **20**:101-111.

Woodey, J. C. 1987. In-Season management of Fraser River Sockeye Salmon (*Oncorhynchus nerka*): meeting multiple objectives. Pages 367-374 *in* H. D. Smith, L. Margolis, and C. C. Wood, editors. Can. Spec. Publ. Fish. Aquat. Sci.

Xie, L. S. and W. W. Hsieh. 1989. Predicting the return migration routes of the Fraser-River sockeye salmon (*Oncorhynchus-nerka*). Canadian Journal of Fisheries and Aquatic Sciences **46**:1287-1292.

Xie, Y. B. 2000. A range-dependent echo-association algorithm and its application in split-beam sonar tracking of migratory salmon in the Fraser River watershed. Ieee Journal of Oceanic Engineering **25**:387-398.

Young, J. L., S. G. Hinch, S. J. Cooke, G. T. Crossin, D. A. Patterson, A. P. Farrell, G. Van der Kraak, A. G. Lotto, A. Lister, M. C. Healey, and K. K. English. 2006. Physiological and energetic correlates of en route mortality for abnormally early migrating adult sockeye salmon (*Oncorhynchus nerka*) in the Thompson River, British Columbia. Canadian Journal of Fisheries and Aquatic Sciences **63**:1067-1077.

Zar, J. H. 1996. Biostatistical Analysis. 3rd Ed. edition. Prentice Hall, Inc., Upper Saddle River, New Jersey.

Table 1-1. Example of management adjustment data and calculations of errors in forecasts of models. The first row contains a hypothetical case example of actual abundances (in thousands of fish) and calculated variables used to evaluate the model forecasts. Potential spawning escapement (*PSE*) is calculated each year by subtracting the forecasted in-river catch (C) from the abundance estimate obtained at the Mission sampling location (M). Later in the season when the actual observed spawning escapement (*SE*) is estimated, that value is used to calculate the in-river loss by subtracting the *SE* from the *PSE*. The difference between estimates (DBE) is the natural log of the *SE* divided by the *PSE*. The last two rows contain two hypothetical examples of model forecasts and their outcomes. Each year models forecast a DBE that produces the forecasted *SE*/*PSE* and a forecasted *SE* based on a predicted *PSE*. Once the actual spawning escapement has been observed, the model forecasts are evaluated by subtracting the observed *SE*/*PSE* from the forecasted *SE*/*PSE* to produce the raw error (*RE*) and by determining the outcome of the model forecast compared to the actual in-river loss; the latter actual loss is the ideal management adjustment. Finally, these calculations assume both (1) that the management adjustment applied to the fisheries is the same as the forecasted management adjustment, and (2) that the error in terms of achieving the spawning escapement target is equivalent to the difference between the spawner abundance from the management adjustment forecast and the actual spawner abundance the forecasted spawner abundance is compared to the spawning escapement target.

Table 1-1

	Potential spawning escapement (*PSE*)	Mission total abundance estimate (M)	Forecasted in-river catch (C)	Actual spawning escapement (*SE*)	In-river loss (*PSE-SE*)	Difference Between Estimates (DBE) Ln(*SE*/*PSE*)	Observed *SE*/*PSE*
Actual	400	500	100	350	50	-0.134	0.875

	Forecasted DBE Ln(*SE*/*PSE*)	Forecasted *SE*/*PSE*	Raw Error (*RE*)	Forecasted SE (if *PSE* = 400)	Estimate of in-river loss by MA model	Management Adjustment estimated by MA model	Actual spawners compared to spawning escapement target
Forecast (Model 1)	-0.078	0.925	0.05	370	30, Underestimate (U)	Too small	Below target
Forecast (Model 2)	-0.192	0.825	-0.05	330	70, Overestimate (O)	Too big	Above target

Table 1-2. Management Adjustment models. *T* is the 31-day average river temperature measured at Qualark (^{o}C) in the lower Fraser River symmetrically centered on the Hells Gate 50% date (i.e., the date at which 50% of the run has migrated past Hells Gate). *Q* is the 31-day average discharge measured at Hope (m^3/s) symmetrically centered on Hells Gate 50% date. D_{50} is the date when 50% of a run has passed Hells Gate. *H* is the historical average DBE (the historical difference between estimates of upriver spawning escapement abundance and lower-river potential spawning escapement abundance estimates), *n* is calendar year, and the *a* and *b* parameters are the best-fit regression parameters that result from fitting each of the models in each year of the retrospective analysis. The symbol for each model is used as an abbreviation for the full model name within the text.

Table 1-2

Equation	Symbol	Model Variables (Model Name)	Equation
1	T	Temperature (Temperature)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1T + b_2T^2$
2	Q	Discharge (Discharge)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1Q + b_2Q^2$
3	T+Q	Temperature-plus-discharge (Temperature-plus-discharge)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1T + b_2T^2 + b_3Q + b_4Q^2$
4	R	Run-timing date (Run-timing)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1D_{50}$
5	H	Average historical DBE (Historic)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1H$ $H = \frac{\sum_{n=1977}^{N} observed \ln(SE/PSE)_n}{N}$
6	NMA	None (No Management Adjustment)	$\ln\left(\frac{SE}{PSE}\right) = 0$

Table 1-3. AIC_c values and their components for each model in each run-timing group. MLL = mean maximum log likelihood, K = number of parameters AIC_c = mean small-sample Akaike information criterion, Δ AIC_c = mean delta AIC_c, and Weight = mean AIC_c weight.

Run Group	Model	MLL	K	AIC_c	Δ AIC_c	Weight
Early Stuart	Temperature	-13.96	4	39.01	0.49	33.40%
	Discharge	-15.87	4	42.84	4.31	4.94%
	Temperature-plus-discharge	-10.51	6	40.85	2.33	13.32%
	Run-timing	-17.50	3	42.71	4.19	5.26%
	Historic	-15.41	3	38.52	0.00	42.64%
	No MA	-22.72	1	47.69	9.16	0.44%
Early Summer	Temperature	-9.12	4	28.57	6.10	4.00%
	Discharge	-8.59	4	27.50	5.03	6.86%
	Temperature-plus-discharge	-6.53	6	30.64	8.16	1.43%
	Run-timing	-10.90	3	29.12	6.65	3.05%
	Historic	-7.58	3	22.47	0.00	84.64%
	No MA	-18.35	1	38.89	16.42	0.02%
Summer	Temperature	0.21	4	9.80	0.00	71.57%
	Discharge	-4.40	4	19.02	9.22	0.71%
	Temperature-plus-discharge	0.68	6	15.92	6.12	3.36%
	Run-timing	-5.35	3	17.95	8.15	1.21%
	Historic	-3.25	3	13.75	3.96	9.90%
	No MA	-5.49	1	13.17	3.37	13.24%
Late	Temperature	-11.27	4	42.05	25.10	0.00%
	Discharge	-5.86	4	27.65	10.69	0.47%
	Temperature-plus-discharge	-2.13	6	47.19	30.24	0.00%
	Run-timing	-2.69	3	16.96	0.10	98.53%
	Historic	-7.71	3	26.55	9.59	0.81%
	No MA	-14.20	1	29.47	12.51	0.19%

Table 1-4. Percentage of years in the jack-knife analysis in which a model other than the top-ranked model from the retrospective analysis model ranked first, by performance measure and run-timing group of Fraser sockeye salmon. The performance measures are mean raw error (MRE), mean absolute error (MAE) and root mean square error (RMSE).

Performance Measure	Early Stuart	Early Summer	Summer	Late
MRE	15%	23%	17%	9%
MAE	46%	8%	0%	0%
RMSE	54%	23%	8%	9%

Figure 1-1. Fraser River map showing data-collection points and spawning locations. Dates in the legend are the historic median Hells Gate 50% run-timing dates for each run-timing group.

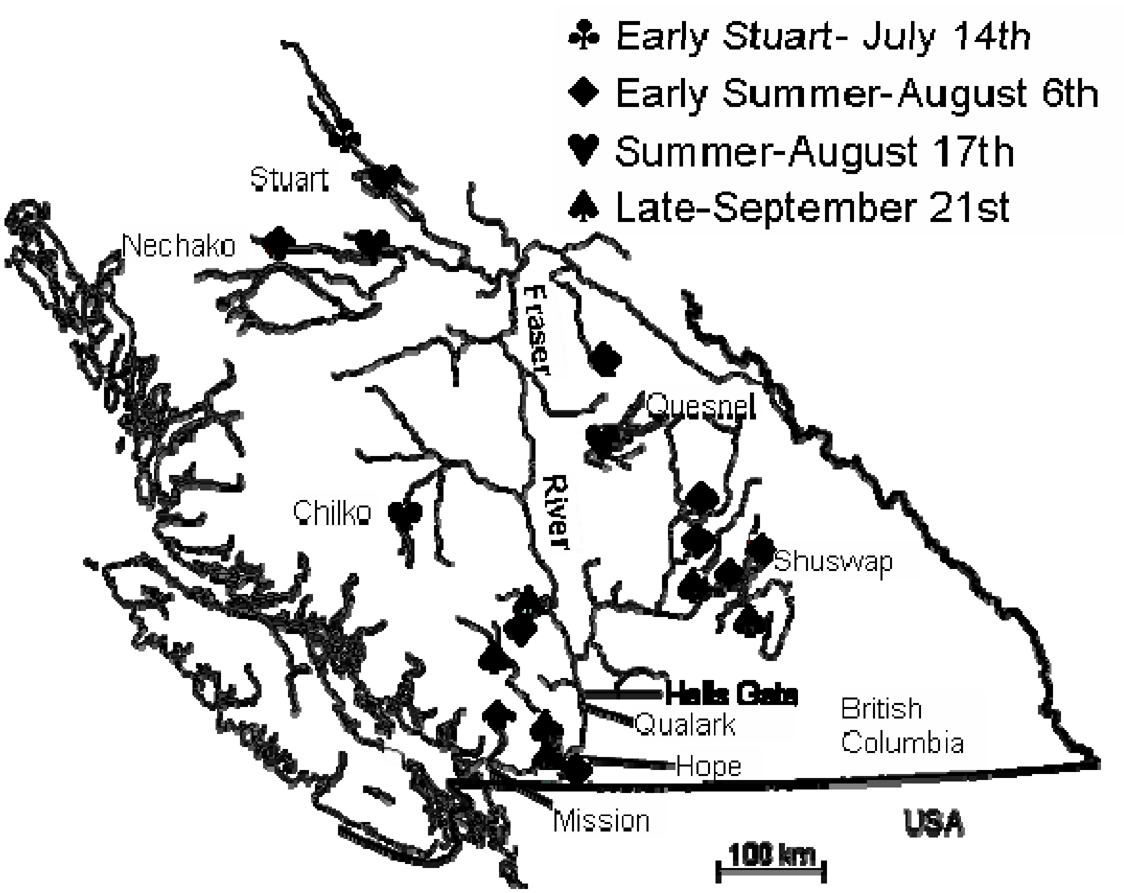
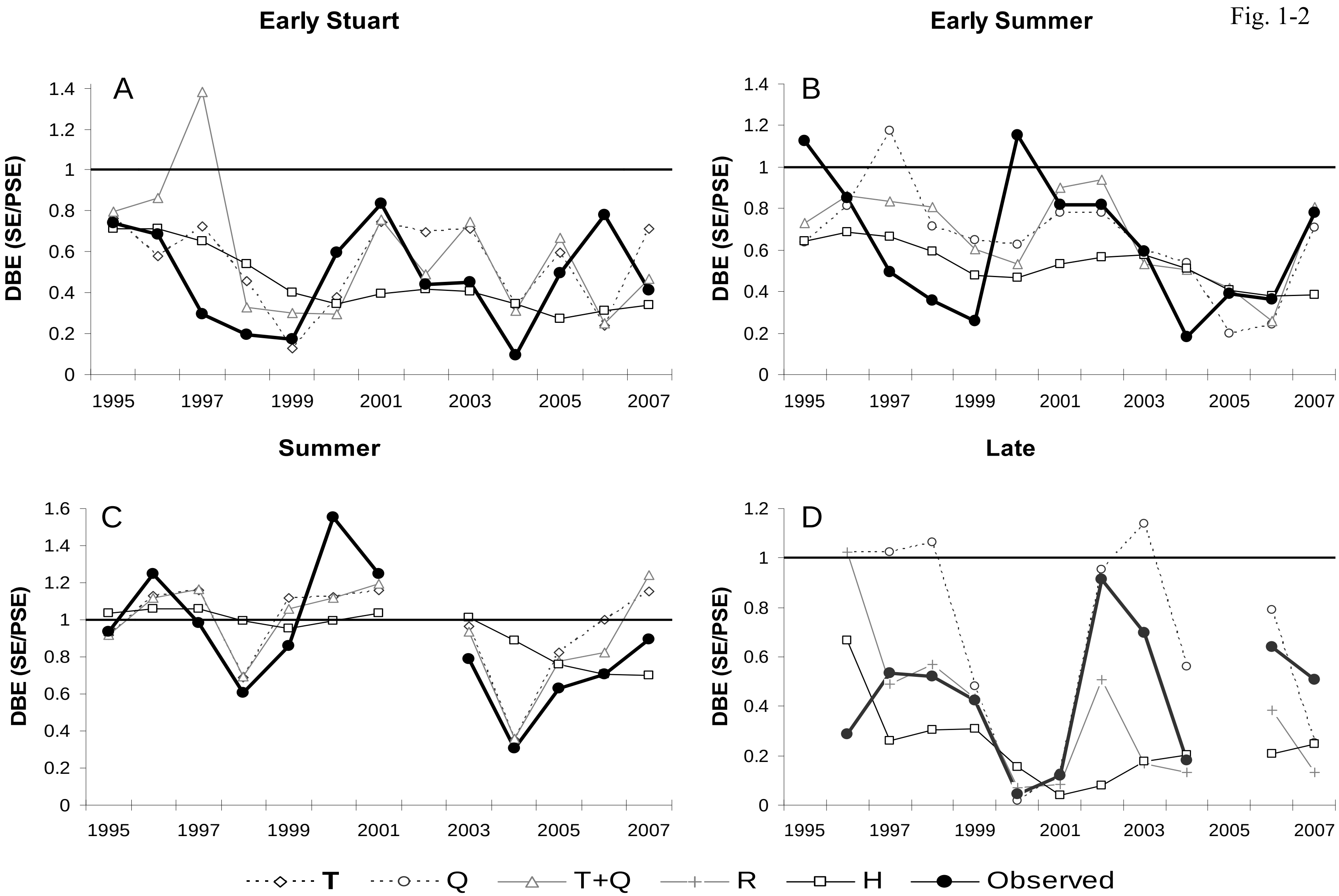


Figure 1-2. Difference between estimates (DBEs) of escapement of Fraser River sockeye salmon, by run-timing group, where DBE = SE (spawning escapement estimate)/PSE (Mission potential spawning escapement estimate). Observed escapement discrepancies (Observed) are shown along with forecasts of the three top-ranked models for each run-timing group based on the average model rank (Fig. 1-4). SE= spawning escapement estimate, PSE= Mission potential spawning escapement estimate, T = temperature model, Q = discharge model, T+Q = temperature plus discharge model, R = run-timing model, and H = historic model. A DBE of one indicates no in-river loss of upstream-migrating adult sockeye salmon, while a DBE of zero indicates 100% in-river loss.

Fig. 1-2



Early Stuart
A
Early Summer
B
Summer
C
Late
D
DBE (SE/PSE)
1995
1997
1999
2001
2003
2005
2007
T
Q
T+Q
R
H
Observed

Figure 1-3. Average value of each performance measure for each model over the 13-year evaluation period. Note that the scale of the vertical axis varies with run-timing group. Model labels are: T = temperature model, Q = discharge model, T+Q = temperature-plus-discharge model, R = run-timing model, H = historic model, NMA = no management adjustment model. Performance measures are: MRE = mean raw error, MAE = mean absolute error, RMSE = root mean square error, R^2 = adjusted R^2.

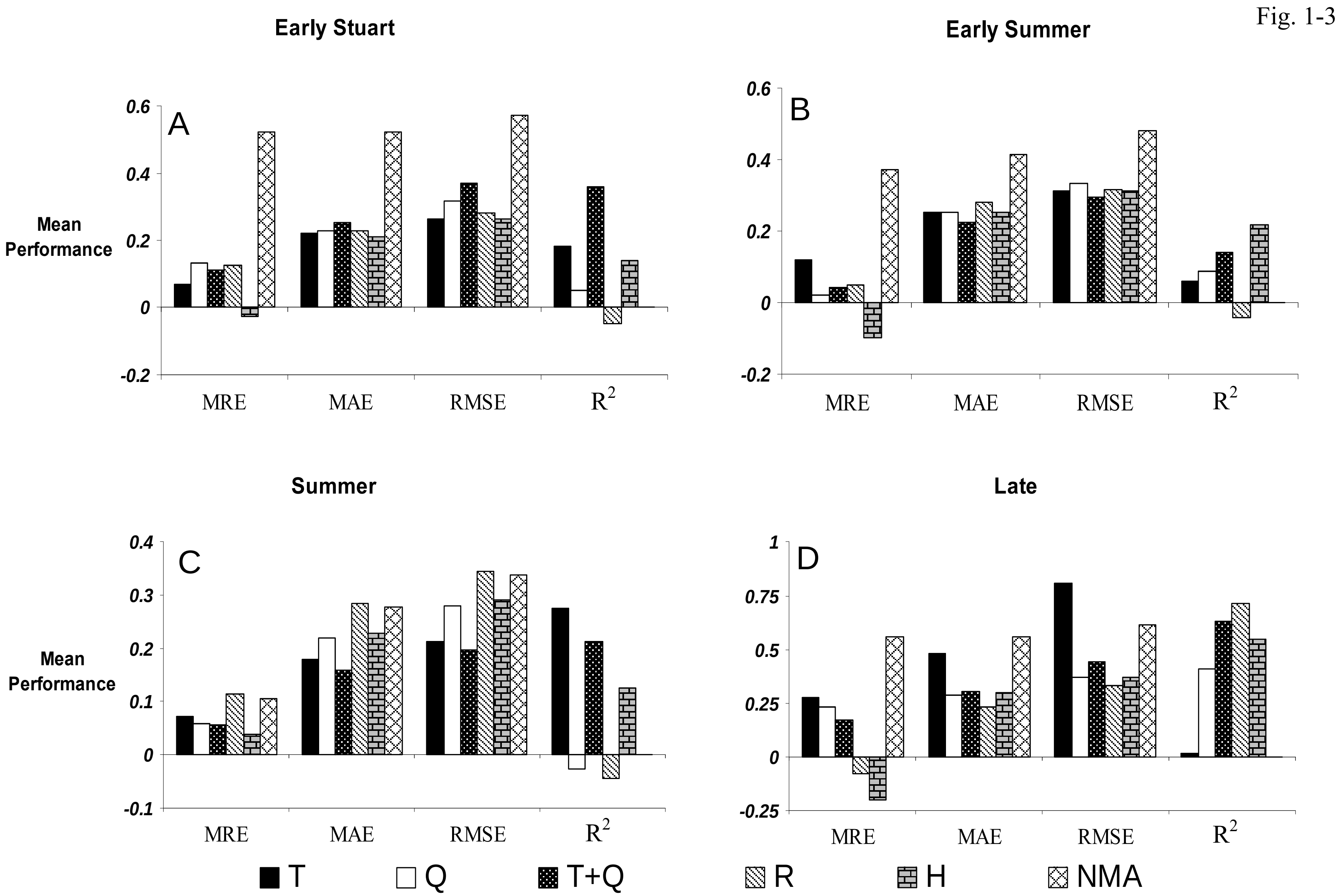


Fig. 1-3
Early Stuart
A
Mean Performance
0.6
0.4
0.2
0
-0.2
MRE
MAE
RMSE
R2
Early Summer
B
0.6
0.4
0.2
0
-0.2
MRE
MAE
RMSE
R2
Summer
C
Mean Performance
0.4
0.3
0.2
0.1
0
-0.1
MRE
MAE
RMSE
R2
Late
D
1
0.75
0.5
0.25
0
-0.25
MRE
MAE
RMSE
R2
T
Q
T+Q
R
H
NMA

Figure 1-4. Average rank of each management adjustment model, where averages were taken across the rankings based on each of the five performance measure ranks and where the individual performance measure rank was based on a 13-year average. The model with the best average across performance measures achieved the average closest to one, and the worst an average closest to six. Model and run-timing group labels are the same as in Figure 1-3.

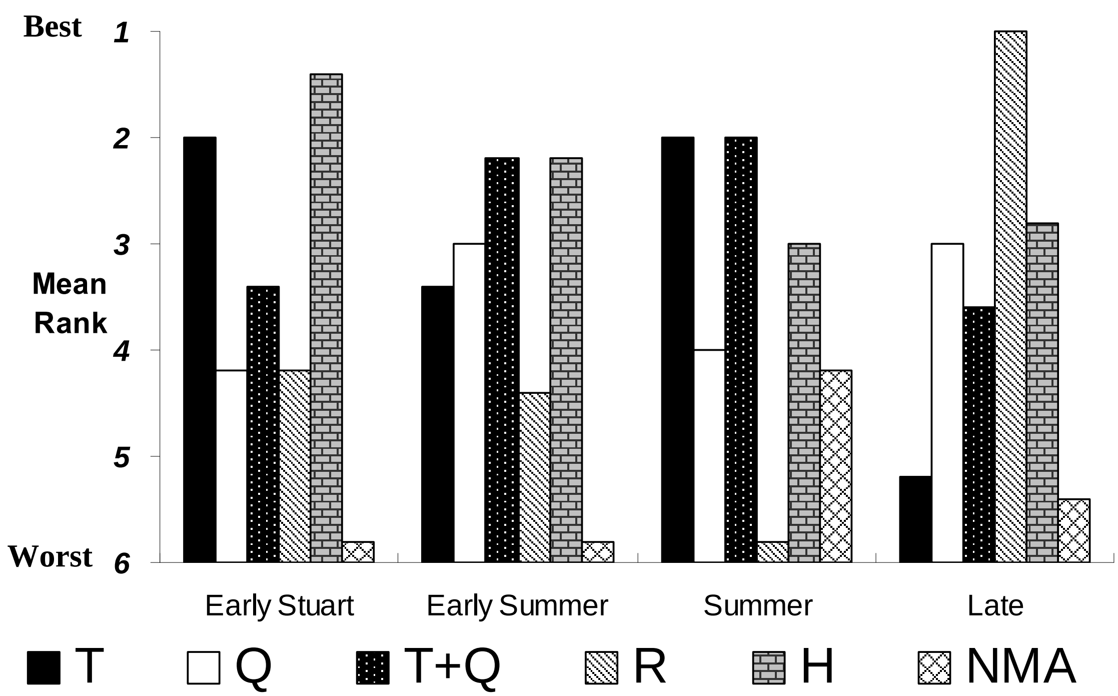


Figure 1-5. Management adjustment models ranked by performance measure. This figure breaks down the run-timing group results from Figure 1-4 by performance measure. The rank of each MA model is determined relative to the performance of the other models for a given performance measure, with one being the best rank and six being the worst. Performance measures are: MRE = mean raw error, MAE = mean absolute error, RMSE = root mean square error, R^2 = adjusted R^2, and AIC_c = small-sample Akaike information criterion. Model labels are: T = Temperature model, Q = Discharge model, T+Q = Temperature-plus-discharge model, R = Run-timing model, H = Historic model, NMA = No management adjustment model.

Fig. 1-5

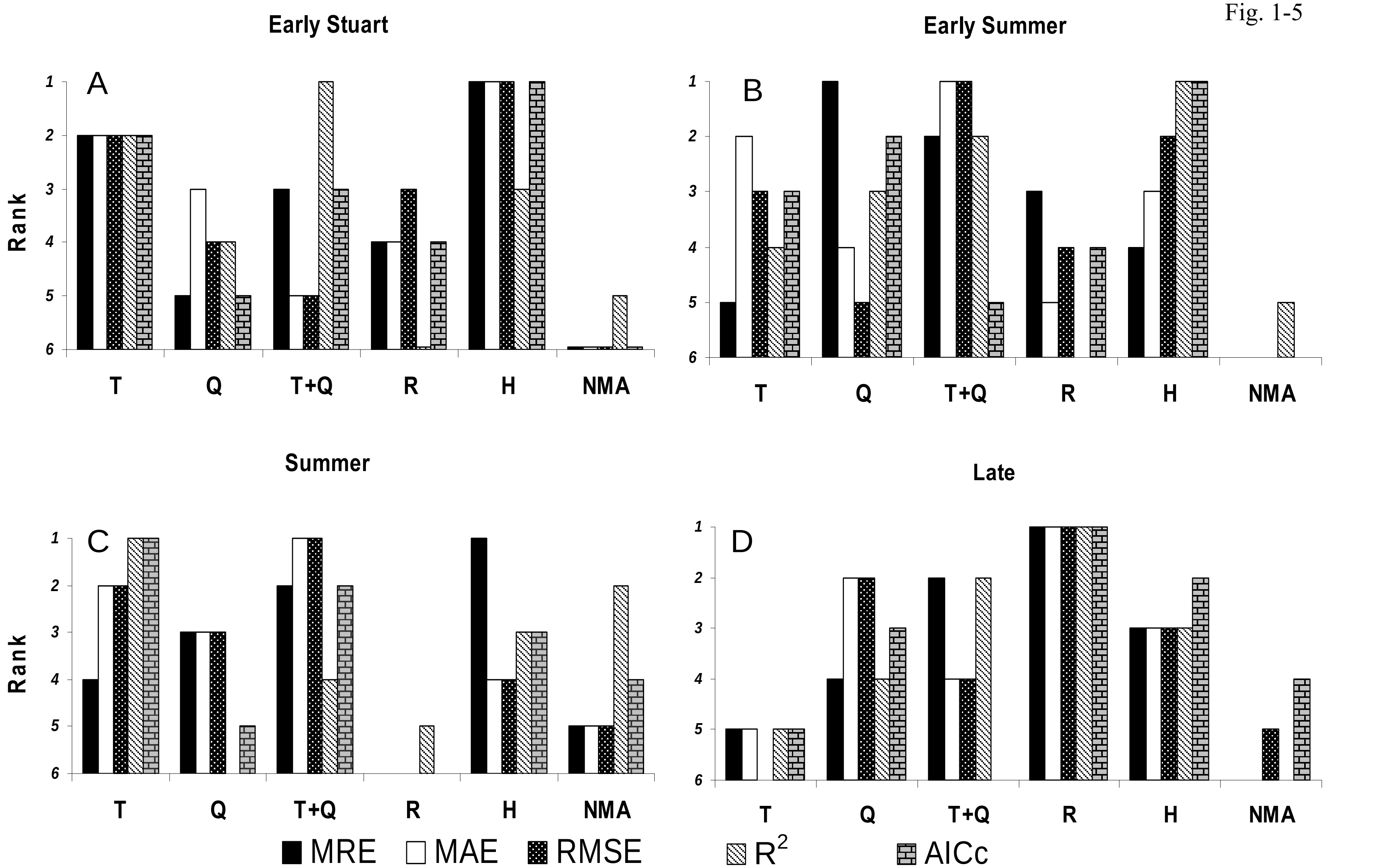

Early Stuart
A
Rank
1
2
3
4
5
6
T
Q
T+Q
R
H
NMA
Early Summer
B
1
2
3
4
5
6
T
Q
T+Q
R
H
NMA
Summer
C
Rank
1
2
3
4
5
6
T
Q
T+Q
R
H
NMA
Late
D
1
2
3
4
5
6
T
Q
T+Q
R
H
NMA
MRE
MAE
RMSE
R^2
AICc

Figure 1-6. ΔAIC_c, or average AIC_c of each model minus the AIC_c of the model with the best AIC_c for each run-timing group. The vertical line at $\Delta AIC_c = 2$ corresponds to the typical separation between models with substantial levels of empirical support and those with considerably less (Burnham and Anderson 2002). Model labels as in Figure 1-3; letter in blank areas of histogram indicate which model has the lowest AIC_c.

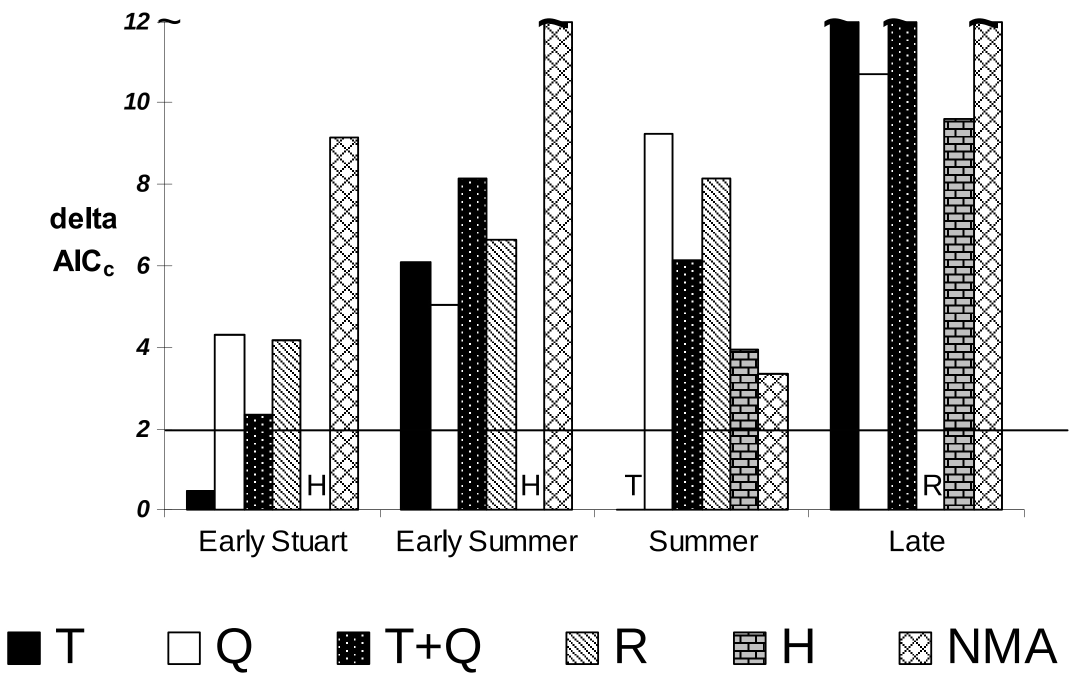


Figure 1-7. Frequency of best performance, shown as the number of years for which each management adjustment model was best, i.e., produced the smallest raw error (*RE*, equation 7) relative to the *RE* of other models. For comparison, the number above each bar is the average model rank from Figure 1-4.

Fig. 1-7

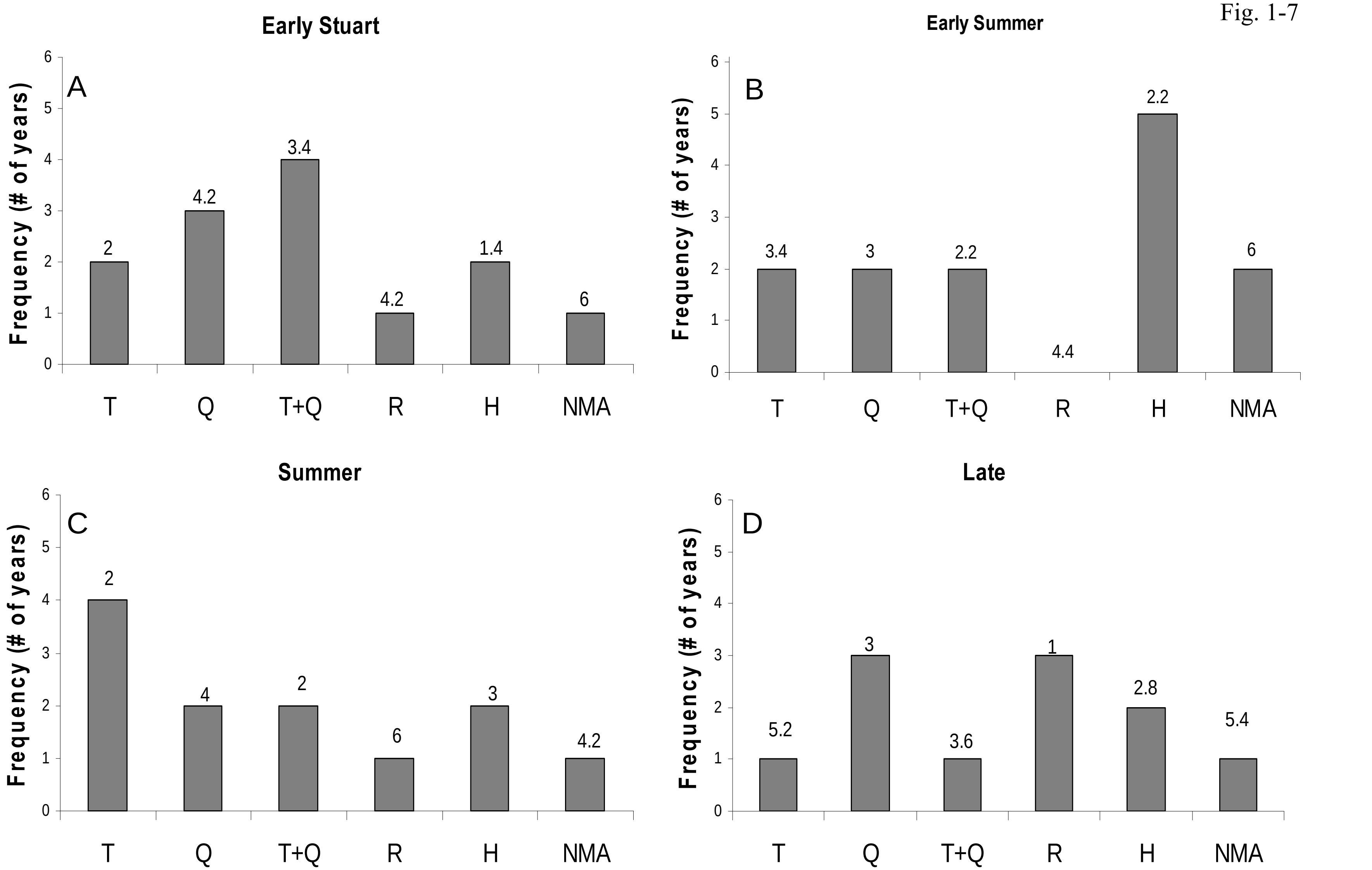

Early Stuart
A
Frequency (# of years)
0
1
2
3
4
5
6
2
4.2
3.4
4.2
1.4
6
T
Q
T+Q
R
H
NMA
Early Summer
B
Frequency (# of years)
0
1
2
3
4
5
6
3.4
3
2.2
4.4
2.2
6
T
Q
T+Q
R
H
NMA
Summer
C
Frequency (# of years)
0
1
2
3
4
5
6
2
4
2
6
3
4.2
T
Q
T+Q
R
H
NMA
Late
D
Frequency (# of years)
0
1
2
3
4
5
6
5.2
3
3.6
1
2.8
5.4
T
Q
T+Q
R
H
NMA

Figure 1-8. Average rank from 1 to 8 (1 is best) across three performance measures (MRE, MAE, and RMSE), excluding AIC_c and R^2, for the two alternative forecasting techniques (AIC_c weights and optimized model weights) and the six stand-alone models.

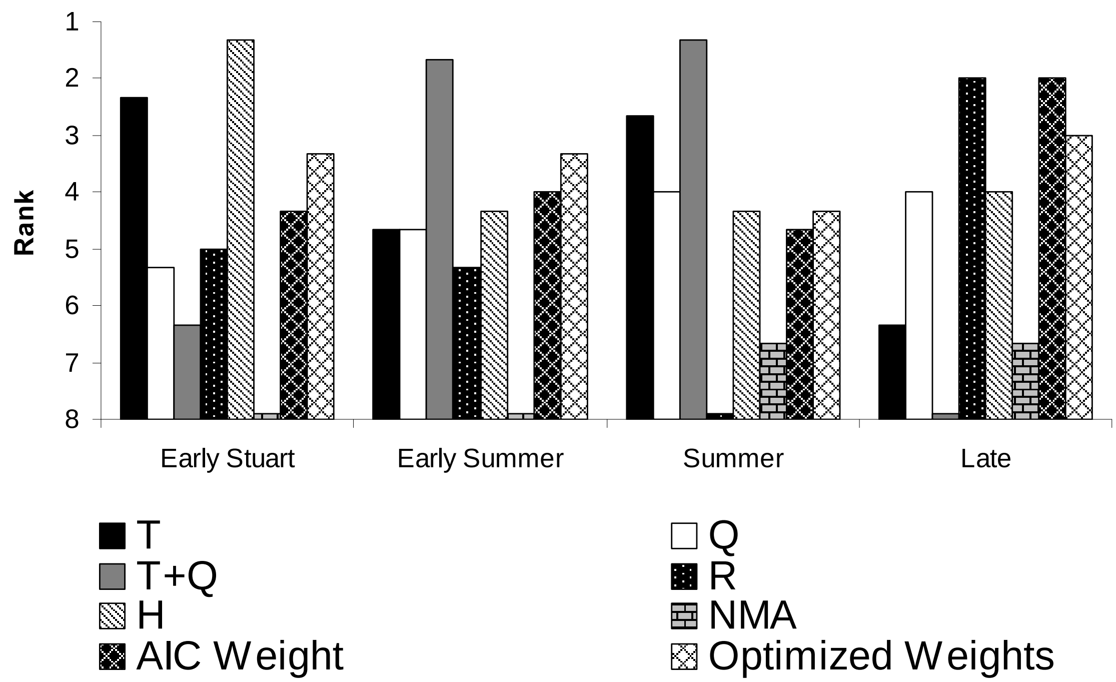
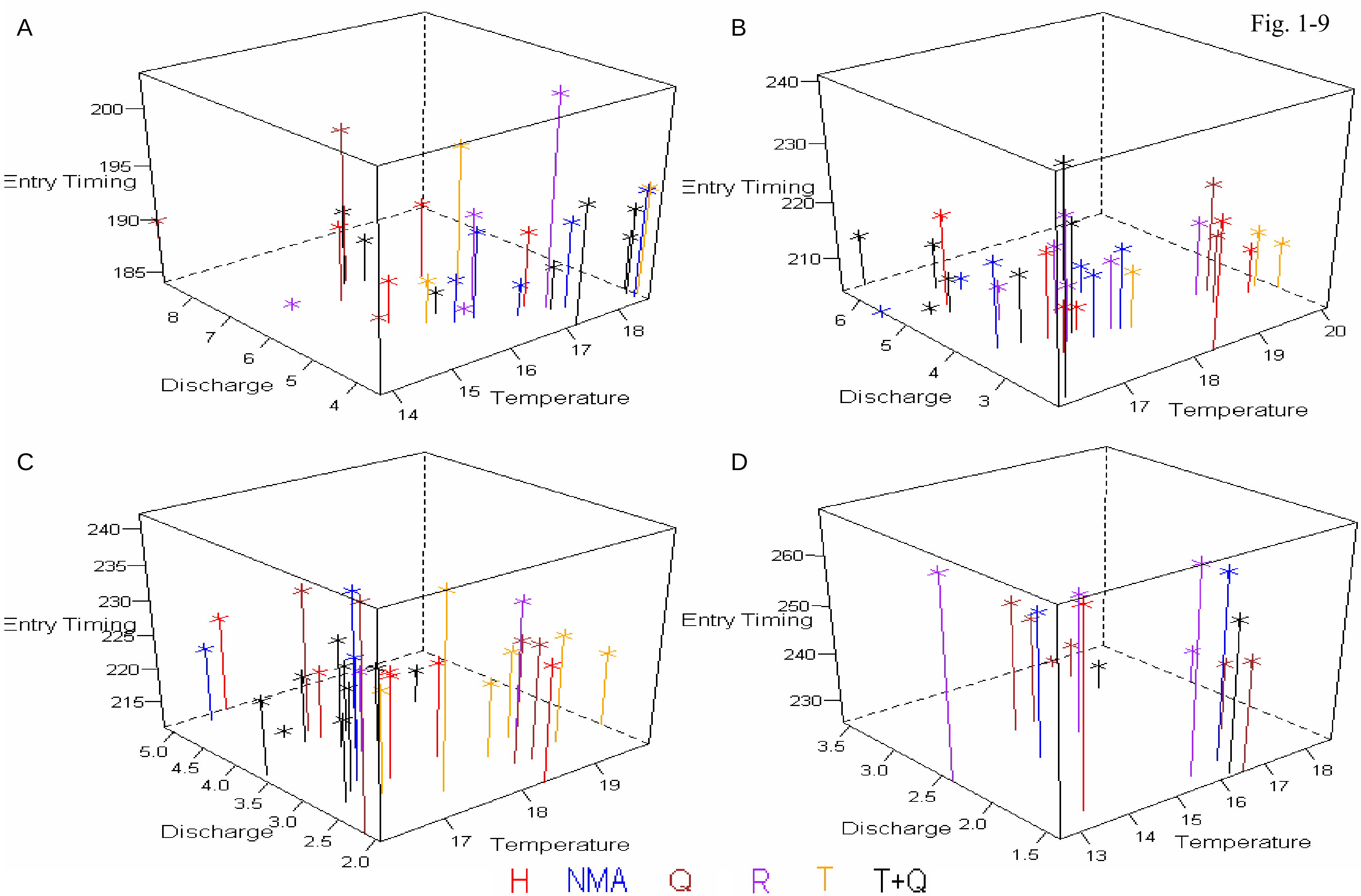


Figure 1-9. Each point represents the best model in terms of raw error (*RE*) in a given year plotted according to the Fraser River temperature and discharge and the run-timing group entry date in that year. Each of the four panels is for a run-timing group A = Early Stuart, B = Early Summer, C = Summer, D = Late. Temperature is in degrees Celsius, Discharge is in thousands of cubic meters per second, and Entry Timing is day of the year at which 50% of the run-timing group reached Hope. Model labels are: H (red) = Historic model, NMA (blue) = No MA model, Q (brown) = Discharge model, R (purple) = Run-timing model, T (yellow) = Temperature model, and T+Q (black) = Temperature-plus-discharge model.

Fig. 1-9



CHAPTER 2: ANALYSIS OF ASYMMETRIC LOSS FUNCTIONS

Introduction

Managers of Pacific Salmon (*Onchorhynchus spp.*) fisheries often face a trade-off between achieving target spawning escapements and allowing a substantial harvest. After they determine fisheries management objectives, managers select targets for spawning escapement and total allowable mortality that create acceptable trade-offs. Such targets are typically set based on analyses with models, but numerous uncertainties pervade these models and limit managers' abilities to make accurate predictions and achieve management targets regularly. Selection of models that are robust to a wide range of uncertainties can therefore assist managers. However, traditional methods for model selection (Christoffersen and Diebold 1996, Burnham and Anderson 2002) do not take into account the asymmetric cost function that managers might perceive from outcomes arising from model forecasts. For instance, a given salmon manager might be twice as concerned about having 500,000 fewer spawners than desired than 500,000 too many (the later implying lower catches), but other managers might have the reverse preference. Thus, a given model used to help set regulations that tends to lead to too few spawners might be ranked differently by these two groups of managers. I address this gap by exploring the effect of asymmetric loss functions on the rank order of management adjustment (MA) models. Managers use these MA models in the management of Fraser River sockeye salmon (*O. nerka)* in British Columbia to adjust fishing regulations according to forecasts of in-river losses of upstream migrating adults.

The Fraser River Sockeye Salmon System

Sockeye salmon in British Columbia's Fraser River system are managed to best achieve spawning escapement targets, as outlined in bilateral agreements such as the *Pacific Salmon Treaty* (1985) and Canadian policies such as the *Oceans Act* (1996) that list sustainability as a primary objective of fisheries management. Fraser River sockeye salmon management is the ultimate responsibility of Fisheries and Oceans Canada (DFO), but this responsibility is delegated to the bilateral (Canada and U.S.) Fraser River Panel during in-season management periods, with the primary goal of achieving spawning escapement targets and secondary objectives of meeting harvest goals as laid out in the *Pacific Salmon Treaty* (Shepard and Argue 2005). This established hierarchy of goals inherently places higher priority on meeting spawning objectives than on harvest objectives.

A major complication to achieving this balance between spawning and harvest objectives is that adult sockeye salmon can periodically experience unexpectedly high levels of mortality during their freshwater upstream migration to the spawning grounds, i.e. en-route mortality (Macdonald 2000, Cooke et al. 2004, Cooke et al. 2006, Crossin et al. 2008). For example, indices of in-river loss, which are calculated from sockeye salmon abundances that are estimated at Mission but that are not found subsequently upriver in spawner abundance estimates (Fig. 2-1 for locations), have exceeded half a million fish in 8 of the past 16 years (Patterson et al. 2007b). These extreme events have commonly been associated with extreme migration conditions such as high water temperatures and flows (Macdonald et al. 2000, Rand et al. 2006). Therefore, in addition to setting spawning escapement targets that implicitly assign fish to either harvest or spawning grounds according to fisheries objectives, effective management of the Fraser River sockeye salmon fishery in any given year depends, in part, on precise and unbiased forecasts of in-river loss. Forecasts of in-river loss are made using management adjustment (MA) models and are used to reduce total allowable catch to account for expected in-river loss, thereby increasing the likelihood of meeting management objectives such as spawning targets (Chapter 1, Macdonald et al. 2009, in review).

However, partially due to errors in forecasts of appropriate MAs, actual realized spawning escapements generally differ from targets at the end of the season. Most analyses of forecasting efficacy of various management models only evaluate forecasts based upon statistical characteristics of their error (bias, precision, frequency of extreme values, etc.), but the true "cost" of those errors depends on interpretation of those errors as well as forecast accuracy and precision. As described later in the methods section, loss functions help by translating forecast error into a complete analysis of model efficacy by connecting the error of a forecast, and the resulting difference between a target and an actual value to the cost to individuals or groups using the forecast. Loss functions depend on characteristics of the system being forecasted (sockeye salmon in the Fraser River), forecast error (from the management adjustment model), and user preferences (the objectives of Fraser River sockeye salmon fisheries managers).

I will use the following conventions in discussions of asymmetric loss functions. For simplicity, this analysis will discuss model forecasts of in-river losses of upstream migrating adults compared to observed in-river losses (Table 2-1). Therefore, a forecast will be described as either an overestimate or an underestimate of the in-river loss, which is quantified as the raw error (*RE*) of a forecast. Management objectives will be phrased in terms of managers' preferences, with managers either favoring spawning or harvest goals. Loss functions will convert error into a perceived "cost", not necessarily financial, which is quantified as the lost value (*LV*) of the forecast, so it is important to note that favoring spawning means that failing to obtain a spawner abundance as high as a spawning objective is the more costly of the two types of forecast error. For example, when managers favor spawning, the cost of having fewer spawners than the target arrive on the spawning grounds is larger than the cost of harvesting too few fish, and the converse is true when managers favor harvest (Table 2-1, Fig. 2-2).

Forecast Error

Even the best ecological models do not produce perfect forecasts, and this is also true of models used for estimating in-river losses of upstream migrating adult sockeye salmon in the Fraser River. These imperfect estimates can be quantified in terms of the size of the error, i.e., the degree to which the forecast was different from the observed in-river loss, and the direction of the error, i.e., either an overestimate or an underestimate of the in-river loss. In this study, error is quantified using raw error (*RE*), (Table 2-1 and Methods-*Model forecast error*). Once the error has been quantified, it can be placed in the context of the fisheries; for example, an overestimate of in-river loss would result in greater-than-necessary reduction in harvest and both less harvest and more spawners than stated in the objectives. In contrast, an underestimate of in-river loss would result in too many fish being harvested, causing too few fish to reach the spawning grounds to achieve escapement targets (Table 2-1).*

Management Objectives

Salmon fisheries managers must choose between meeting spawning objectives designed to support ecological needs, such as the sustainability and biological diversity of the populations, and harvest objectives designed to support social and short-term economic needs, such as subsistence, recreation, and employment income. While the managers' actual preferences and resulting asymmetric loss functions are usually unknown, it is reasonable to assume that such preferences are likely to be asymmetric because of competing interests managers face when making management decisions. For instance, when managers favor spawning, they view exceeding harvest objectives as more costly than exceeding spawning targets, whereas a manager who views exceeding spawning objectives as more costly than exceeding harvest objectives favors the latter. Either of these possible asymmetries in management preferences can be represented by a loss function which, based on preferences of managers or of users, can convert forecast errors, i.e., *RE*, into the value lost (lost value (*LV*)) due to forecast error.

Asymmetric Loss Functions

Standard methods of comparing one model's forecasts with subsequent actual outcomes use squared deviations, e.g., sum of squares, likelihood, or root mean square error, which assume symmetry in the loss function. However, the assumption of

* These last two statements are based on two simplifying assumptions; one, that the management adjustment applied to the fisheries is the same as the forecasted management adjustment, and two, the error in terms of achieving the spawning escapement target is equivalent to the difference between the spawner abundance from the management adjustment forecast and the actual spawner abundance.

symmetry by standard methods can be problematic if there actually are asymmetric costs associated with exceeding or falling below an objective (Walters and Martell 2004).

Chapter 1 ranked Fraser River sockeye salmon management adjustment models based on such standard symmetric performance measures. Those models were ranked using mean raw error, mean absolute error, root mean square error, small sample Akaike information criterion (AIC_c), and adjusted R^2. Based on average rank across these five performance measures, the historic model was best for the Early Stuart run-timing group, the historic and the temperature-plus-discharge models tied for highest rank for the Early Summer run, the temperature and the temperature-plus-discharge models tied for best for the Summer run, and the run-timing model was best for the Late run. However, these rankings might change if asymmetric losses are considered.

The consideration of asymmetric loss functions in fisheries is supported by work in the environmental, economic, and forecasting fields. For example, economic analysis has moved toward the realization that one's point of reference and the direction of a change are important in determining both the economic value of that change and the likelihood that buyers and sellers will make a transaction. Economic researchers have found that individuals are willing to pay much less to obtain a good than they demand to be compensated in order to give up that same good or service if they possess it (Knetsch and Sinden 1984, Knetsch 1995b). This finding is supported by studies demonstrating that economists and forecasters often make biased forecasts because of the asymmetric costs of forecast error (Goodwin 2005, Lawrence and O'Connor 2005). All of these results have important implications for the evaluation of management strategies and forecasts, particularly in the case of environmental goods and services (Knetsch 1990), because failing to account for the discrepancy between willingness to pay and compensation demanded can lead to improper assessments of the value of management actions, project proposals, and damage settlements that undervalue environmental goods (Knetsch 1995a, 2007). All of these examples point to the need to include an analysis of the effect of asymmetric costs on behavior during the development and evaluation of resource management policies. To address this need, Elliott and Timmermann (2008) suggest the use of asymmetric loss functions for evaluation of economic forecasts, in part based on theoretical studies showing that optimal forecasts under asymmetric loss conditions differ from optimal forecasts under symmetric loss conditions (e.g., Granger 1969, Zellner 1986, Christoffersen and Diebold 1996, 1997, Granger and Pesaran 2000, Patton and Timmermann 2007).

Ecological and environmental researchers also are aware of the presence of asymmetric losses (Reckhow 1994, Frederick and Peterman 1995, Walters and Martell 2004), but asymmetric losses have rarely been directly addressed or formally evaluated in ecology. The research that has been conducted points to the prevalence of asymmetric loss as a justification for the incorporation of uncertainty in decision making. For example, Reckhow (1994) recommends formal quantitative decision analysis in order to incorporate the impacts of asymmetric loss into the decision making process and shows how including safety factors can avoid high-cost outcomes. Walters and Martell (2004) recommend closed loop simulations to evaluate the impacts of asymmetric costs on fisheries harvest policies, and Frederick and Peterman (1995) also address the importance of including uncertainty and asymmetric losses in fisheries management. Adkison (2009) suggests that models using decision-analysis approaches are more robust to asymmetric loss functions than models selected using maximum-likelihood approaches. These examples illustrate the need to consider asymmetric loss functions in models of fisheries management systems.

Loss functions combine user preferences with the direction and magnitude of forecasting errors to determine the expected (i.e., weighted average) cost of a forecast to that user. The loss function takes the raw error (*RE*) of a forecast as an input, adjusts the raw error based on management attitudes, and produces the forecast cost (lost value (*LV*), Table 2-1). Mathematically, the loss from a forecast is a function of the forecast error and management objectives (Granger 1969, Frederick and Peterman 1995). The lost value from the forecast of a model under a particular asymmetric loss function is equal to the magnitude of the error from that model's forecast of in-river loss multiplied by the slope of the asymmetric loss function associated with either overestimating or underestimating in-river loss, depending on the type of forecast error. Therefore, developing the loss function requires determining the attitudes of managers, for example, by identifying the costs they would ascribe to a range of theoretical forecast errors. The function relating those costs to the forecast errors is a loss function (Fig. 2-2). Once managers go through this theoretical process of determining forecast costs from forecast errors, actual forecasts from MA model forecasts of Fraser River sockeye salmon can be evaluated and MA models can be ranked.

For example, if Fraser River sockeye salmon managers follow the recommendations of the *Oceans Act* (1996), then their priority is to first achieve their spawning objectives and then allocate harvest. In such cases, managers should have an asymmetric loss function that weights losses from forecast errors resulting in additional harvest beyond the target catch more heavily than errors resulting in more spawners than the spawning target i.e., an asymmetric loss function indicating managers favor spawning objectives (Fig. 2-2C). It is also possible that, given both the economic interests and political influence of harvest groups, managers may tend to favor allowing extra harvest at the risk of not always meeting spawning targets, which would imply an asymmetric loss function in the opposite direction, i.e., treating forecasting errors that result in spawner abundances above the target abundance as more costly than errors that result in harvest above the target catch. In the latter case, managers would favor harvest objectives (Fig. 2-2A).

The objective of this research is to evaluate the impact of a range of possible management preferences for competing objectives, especially those preferences that produce asymmetric loss functions, on the cost of utilizing any one of several management adjustment models for Fraser River sockeye salmon. This analysis of models for Fraser River MA forecasting aims to evaluate multiple models' forecasts in the presence of asymmetric loss by assigning a loss to each model in retrospective analyses of how those models would have performed if they had been used in the past. This work should provide additional insight beyond that of previous studies into the impact of asymmetric losses, which have demonstrated that the efficacy of decisions are affected by asymmetric loss functions. Here I provide an example of the impact of asymmetric losses on an actual fishery as opposed to the theoretical and simulation studies of Reckhow (1994) and Frederick and Peterman (1995), respectively. The direction and shape of managers' asymmetric loss functions may have a large influence on their selection of a desired MA model. By exploring a range of asymmetric loss functions, this research can show how asymmetric loss functions affect choices of MA models and the effects of those choices on Fraser River sockeye salmon escapement and harvest. This information may aid managers in both developing an asymmetric loss function that represents their preferences and selecting models that result in minimal losses.

Methods

Data

Annual sockeye salmon abundance estimates at Mission and estimates of sockeye salmon catch upriver of Mission were provided by the Pacific Salmon Commission (PSC) while Fisheries and Oceans Canada (DFO) provided historical spawning escapement estimates for sockeye salmon (DFO stock assessment, T. Cone, Annacis Island, BC). Mission abundance and run-timing estimates were obtained using hydroacoustic sonar (Xie and Hsieh 1989, Xie 2000), whereas spawning ground abundance estimates were obtained through a variety of observation techniques. Fraser River temperatures were collected as part of the Fraser River Environmental Watch Program (Patterson et al. 2007a), and Fraser River flows were measured by Environment Canada's Water Survey of Canada (http://scitech.pyr.ec.gc.ca/waterweb/). Temperature measurements were taken at Qualark, B.C. and the flow measurements were from Hope, B.C. (Fig. 2-1).

Management Adjustment Models

It is necessary to use a proxy for natural mortality of upstream migrating adults because scientists currently lack a direct measure of migration mortality of adult Fraser River sockeye salmon (Patterson et al. 2007b). The proxy is the "difference between estimates" (DBEs), i.e., the difference between estimates of upriver spawning escapement abundance (*SE*) and potential spawning escapement abundance estimates made in the lower river at Mission (*PSE*) (Table 2-1). Potential spawning escapement accounts for the lower river escapement as well as forecasted upriver First Nations and recreational catches. More specifically, the DBE response variable is specified as the natural log of the quantity *SE* divided by *PSE*, ln(*SE*/*PSE*) (Hague and Patterson 2007). The reasons for a log-transformation are: (1) to meet assumptions of homoscedasticity in residuals from the fitted models (Zar 1996), and (2) to constrain predictions of *SE*/*PSE* within a positive range (Macdonald et al. 2009, in review).

Six different MA models (Eq. 1 – 6 in Table 2-2) containing four different predictor variables were used for forecasting adult abundance of Fraser River sockeye salmon. Models 1-3 use either (1) Fraser River temperature (*T*) in degrees Celsius, (2) Fraser River flow, i.e. discharge (*Q*) in cubic meters per second, or both. Model 4 uses (3) migration timing (D_{50}) i.e. the date at which 50% of the run has migrated past Hells Gate, while model 5 uses (4) the observed historical average DBEs (*H*) for forecasting adult abundance of Fraser River sockeye salmon. These models were all compared to cases using no management adjustment, model 6. Run-specific management-adjustment-model parameters were estimated for each of these six candidate MA models by fitting historical DBEs (ln(*SE*/*PSE*)) data to historical, environmental, or run-timing conditions using equations in Table 2-2.

Retrospective Analysis

The *a* and *b* parameters of each model were initially fit to data on annual environmental variables and historical DBEs from 1977 – 1994 using the linear modeling function in the statistical software package R (http://cran.r-project.org/). The resulting models from the 1977 - 1994 data were then used to forecast the DBEs for each model in 1995. In the next iteration, the observed 1995 data on annual environmental variables and historical DBEs were added to the time series, model parameters were re-fit, and the 1996 DBEs were forecasted. Retrospective predictions were made for each year from 1995 – 2007. This resulted in up to 13 iterations for each run-timing group where data was available. Note that because of limited data for the Late run-timing group, the temperature-plus-discharge model needed to be initialized from 1977 - 1997 and evaluated from 1998 – 2007 in order to have more data points than regression parameters.

Model forecast error.-- To facilitate interpretation of results, I converted model error, the difference between the predicted and observed values of ln(*SE*/*PSE*) based on equations 1-6, to "raw error" (*RE*) measured on a linear scale using:

(7) $$RE_{n,i} = \exp(\ln(SE/PSE)_{fore,n,i}) - \exp(\ln(SE/PSE)_{obs,n})\,,$$

where $RE_{n,i}$ is the raw error in year *n* of model *i*, $\ln(SE/PSE)_{fore,n,i}$ is the *forecasted* DBE in year *n*, as forecasted by model *i*, and $\ln(SE/PSE)_{obs,n}$ is the *observed* ln(SE/PSE) in year *n* (Table 2-1). By converting to the linear scale, a positive error of a given magnitude has the same value relative to the observed in-river loss as a negative error of the same magnitude (Table 2-1).

Raw error, *RE*, is a unitless measure of the extent to which the forecasted ratio of actual spawner abundance divided by Mission abundance represents the actual observed ratio. The larger the ratio *SE*/*PSE*, the smaller the in-river loss, assuming negligible estimation error. Because raw error (*RE*) is estimated from forecasted minus actual (observed) values of the exponentiated terms in Eq. 7, positive raw errors represent forecasts of *SE*/*PSE* in the left hand term in Eq. 7 that underestimate the true discrepancy (right-hand *SE*/*PSE* term in Eq. 7) between forecasted and observed escapements (negative bias) (Table 2-1). This situation would result in underestimated management adjustments (i.e., more fish being caught than needed to allow for in-river loss), which would in turn produce fewer than the target number of spawners (Table 2-1). In contrast, negative forecasting raw error values (*RE*) represent forecasts that overestimate the true in-river loss and result in management adjustments that would produce more spawners than necessary to meet the spawning escapement target and therefore a smaller harvest than just matching the spawning objective would have allowed (Table 2-1).

Our measures of forecasting error require some explanation. For example, a *SE*/*PSE* of 1 indicates all fish estimated as potential spawners at Mission were later observed upstream on spawning grounds, whereas a *SE*/*PSE* of 0.5 indicates that only half of those potential spawners were enumerated there. A forecast *SE*/*PSE* of 0.75 would predict that 75% of potential spawners at Mission would reach the spawning grounds (a predicted in-river loss of 25%). If the observed *SE*/*PSE* was actually 0.5 in the latter forecasted situation, i.e., an in-river loss of 50% of the fish, then the positive raw error between forecast and observed *SE*/*PSE* (underestimate in this case) indicates spawning objectives would not have been met (Table 2-1).

Asymmetric Loss Functions

The retrospective evaluation described in Chapter 1 assumes that decision makers have a symmetric loss function such that positive and negative raw errors of MA model forecasts are of equal cost for a given magnitude of error. While this is simple computationally, the results are not likely true reflections of the more complex reality faced by managers. Therefore, to reflect some of the additional considerations of decision makers, this asymmetric loss evaluation places a range of possible hypothetical costs on positive and negative errors rather than treating positive and negative errors equally.

To conduct the asymmetric loss function analysis, I converted raw errors in forecasts of in-river losses into perceived losses relative to perfectly achieved spawning escapement targets (bottom of Table 2-1). This lost value (*LV*) was used to measure the performance of each of six MA models in each run-timing group. This *LV* should reflect the loss that managers perceive from the two types of forecast error, i.e., either foregone harvest from overestimating in-river loss (negative *RE*) or reduced population resilience to future unfavorable conditions and decreased opportunities for future harvest due to low spawner abundance, which would result from underestimating in-river loss (positive *RE*), Table 2-1. Therefore, the result of each asymmetric loss function scenario examined here should reflect the utility lost over the course of the 13-year retrospective analysis from the point of view of decision makers.

To evaluate the impact that managers' preferences have on the selection of MA models, I estimated the loss that would have resulted from applying any one of the six MA models that were evaluated in the retrospective evaluation. I estimated those losses across a wide range of scenarios for the shape of the asymmetric loss function. With a symmetric loss function, one unit of raw error is equivalent to one unit of lost value (*LV*) because over- and underestimates are weighted equally. However, for the asymmetric loss functions used in this analysis, one unit of error for *RE* will result in either greater or less than one lost unit of value (Fig. 2-2A, C). The degree of asymmetry depends on the weighting that managers apply to each objective, which is represented by the slope of the limbs of the asymmetric loss function (Fig. 2-2). The slope of the loss function changes as one varies the costs applied to the forecast errors. For example, a slope of *O* for negative *RE* reflects overestimates of in-river loss by the MA model, and *U* for positive *RE* reflects underestimates of in-river loss (Table 2-1). It is important to emphasize that underestimates of in-river loss of salmon (slope equal to *U*) would produce a management adjustment (reduction in catch) that is not large enough to fully make up for the in-river loss that actually occurs later in the season. This situation would result in fewer sockeye salmon reaching spawning grounds than desired based on spawning objectives for that year (Table 2-1). Conversely, overestimates of in-river loss of sockeye salmon (slope equal to *O*) would lead to harvests below the catch objectives.

The ratio of *O* to *U* represents the lost value resulting from overestimates of in-river loss (negative *RE*) compared to underestimates of in-river loss (positive *RE*) (Fig. 2-3). Therefore, a manager who prefers a season that produces additional harvest beyond the catch objective twice as much as a season in which the harvest did not reach the objective would select an asymmetric loss function with an *O*:*U* ratio of 2 (Fig. 2-2A, Fig. 2-3). In contrast, a manager who is twice as displeased by not reaching spawning objectives compared to unachieved harvest objectives by the same amount would select an asymmetric loss function with an *O*:*U* ratio of 0.5 (Fig. 2-2C, Fig. 2-3). For example, if a manager had an *O*:*U* ratio of 0.5, with an *O* weight of 0.5 and *U* weight of 1, then when a model produces an overestimate with a *RE* of -0.25, the users' lost value is 0.125, and when the model produces an underestimate with a *RE* of 0.25, the lost value is 0.25 (Equation 8).

$$\textbf{(8)}\ LV = \begin{cases} \sum_{n=1995}^{N} \left| RE_n * W_O \right|, & if \quad RE_n < 0 \\ \sum_{n=1995}^{N} \left| RE_n * W_U \right|, & if \quad RE_n > 0 \end{cases}$$

where *RE* is the raw error in year *n* (Equation 7), *W* is the weight applied to the error, using W_O when the raw error is negative and W_U when the raw error is positive, and *LV* is the lost value resulting from the application of a given model over the duration of the evaluation. I applied weights of 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2, 1.4, 1.6, 1.8, and 2.0 sequentially to both arms (*O* and *U*) of the asymmetric loss function, such that all combinations of overestimate (from 0.5 to 2) and underestimate (from 2 to 0.5) weighting combinations were evaluated.

The lost value from the forecast of model *i* under a particular asymmetric loss function is equal to the error from that model's forecast of in-river loss multiplied by the weight of either overestimating or underestimating in-river loss (i.e., a slope of either *O* or *U*), depending on the type of forecast error (Table 2-1). This calculation is made for each forecast in each of the thirteen years of the retrospective analysis to obtain the total retrospective cost of using that model (Equation 8). When both the overestimate and underestimate weighting is equal to one (symmetric), the result is identical to that model's mean absolute error (MAE) performance from Chapter 1.

Because constraints sometimes preclude choosing the best options, the two models that ranked highest out of the six considered were identified for each asymmetric loss function, with a rank = 1 given to the model that minimizes Equation 8. The relative additional cost of selecting the second-best model instead of the top-ranked model was calculated using:

$$\textbf{(9)}\ ALV = \left[\frac{LV_2 - LV_1}{LV_1}\right] \bullet 100$$

where *ALV* is the additional lost value from applying the second-best model relative to that of the best model, LV_2 is the lost value from the second-best model, and LV_1 is from the best model.

Results

The rank order of management adjustment (MA) models is sensitive to the shape of the asymmetric loss function, but that sensitivity varies depending on run-timing group. Specifically, the best model for the Summer run-timing group was insensitive to the range of shapes of asymmetric loss functions, but the best model for the other three run-timing groups changed according to the shape of the asymmetric loss functions (Table 2-3 and Fig. 2-4). Complete tables of results of applying asymmetric loss functions are in Appendix 4.

With a symmetric loss function (O:U = 1), the performance of each MA model is identical to the model's performance using a mean absolute error performance measure, the average of the absolute values of the raw error (Chapter 1 of this thesis, and Fig. 2-4).

Therefore, with a symmetric loss function, the smallest loss occurs from applying the temperature-plus-discharge (**T+Q**) model every year when managing the Early Summer and the Summer run-timing groups, while the historic (**H**) model results in the smallest error for the Early Stuart run-timing group, and the run-timing (**R**) model performs best for the Late run-timing group (Chapter 1 of this thesis).

Early Stuart Run

For the Early Stuart run-timing group, the top-ranked model in terms of the cost of the forecast error is quite sensitive to the shape of the loss function. Within the range of weights examined, three different models perform best. The **H** model is best when there is equal error weighting (a symmetric loss function, or a 1:1 ratio) and when spawning is favored, i.e., an O:U ratio of less than 1, indicating greater loss associated with underestimates of in-river loss (Fig. 2-4A). However, when harvest is favored only slightly over spawning i.e., an O:U ratio between 1.18 and 1.33, indicating greater loss associated with overestimates of in-river loss, the temperature (**T**) model performs best, whereas more heavily favoring harvest objectives over spawning objectives (O:U > 1.33) results in the discharge (**Q**) model performing best (Fig. 2-4A).

It is also important to note the behavior of a given model across the range of asymmetric loss functions for the Early Stuart group. For example, although the historic model ranks best when spawning is favored, it ranks the worst among the six models when harvest is heavily favored (Appendix 4). In addition, although the **Q** model ranks best when harvest is favored, it ranks fourth among the six models when spawning is favored.

For the Early Stuart run-timing group, the additional lost value (*ALV*) of selecting the second-best model instead of the top-ranked one varies considerably, depending on the degree of asymmetry in the loss function (Table 2-3). When managers favor spawning (*O*:*U* ratios less than one depicted to the left), the *ALV* of selecting the next-best model rather than the **H** model varies between an *ALV* of 6% and 33%. However, when harvest is favored (*O*:*U* ratios greater than one on the right in Table 2-3), the *ALV* from the next-best model is quite small, 3% or less (Table 2-3, Appendix 4).

Early Summer Run

For the Early Summer run-timing group, the top-ranked model only changes at the ends of the O:U range (the more extreme asymmetries) (Fig. 2-4B). The **T+Q** model performs best unless there is a strong preference for meeting either spawning or harvest objectives. Only when the preference for harvest is at least 2.09 times greater than the preference for spawning (*O*:*U* ratio of 2.09) does the **T** model perform better than the **T+Q** model (Fig. 2-4B). In the opposite direction, when the preference for spawning is at least 1.48 times greater than the preference for harvest (*O*:*U* ratio of 0.68), the **H** model outperforms the **T+Q** model (Fig. 2-4B).

The ranking of a given Early Summer model is also sensitive to the range of asymmetry in the loss functions (Table 2-3). For example, the **T** model performs best when harvest is highly favored, but ranks fifth out of 6 models when spawning is strongly favored. Likewise, the **H** model performs best when spawning is highly favored, but ranks last when harvest is strongly favored. The **T+Q** model is not as sensitive to the range of asymmetry, however, because harvest must be favored more than four times as strongly as spawning (i.e., beyond the range of asymmetric loss functions considered) for the **T+Q** model to perform worse than second best.

As seen in the Early Stuart run-timing group, the additional cost of using the second-ranked model instead of the best one was correlated with the degree of asymmetry in the loss function. When managers favor spawning (*O*:*U* ratios less than one on the left), the *ALV* of selecting the next-best model (**T+Q**) rather than the **H** model was as great as 30% (Table 2-3). For most of the remaining *O*:*U* ratios, the *ALVs* were less than 10%.

Summer Run

The Summer run-timing group is completely insensitive to the shape of the loss function (Fig. 2-4C). The ranking of the models under a symmetric loss function is the same as the ranking over the entire range of asymmetric loss functions tested. From best to worst they are: **T+Q, T**, **Q**, **H**, **NMA**, **R**. This result is due to the consistency in the direction of the forecast error across the six forecasts. The raw error for a given model is either positive or negative (i.e., the models are consistently biased) for all six models in at least 9 of the 13 years forecasted; therefore, the error weighting shifted the cost of each model's forecast error in the same direction. With a symmetric loss function, the *ALV* of the **T** model's raw error compared to the **T+Q** model's raw error is 12% (Table 2-3). When harvest is favored (*O*:*U* ratios greater than one depicted to the right in Table 2-3), the *ALV* of the **T** model decreases (to a minimum of 8% for the loss functions examined), whereas the cost increases when spawning is favored (*O*:*U* ratios less than one depicted to the left) to a maximum *ALV* of 15% for the loss functions examined.

Late Run

As with the Early Stuart and Early Summer runs, the selection of the top-ranked model for the Late run-timing group also depends upon whether managers favor harvest or spawning. When spawning objectives are heavily favored over harvest objectives i.e., by 3.33 times or more (*O*:*U* ratio of 0.30 or less), the **H** model performs best (Fig. 2-4D). Conversely, favoring harvest objectives over spawning objectives by 1.44 times or more (*O*:*U* ratio of 1.44 or greater) results in the **Q** model performing best. Between these points when objectives are more symmetric -- when spawning objectives are favored over harvest objectives by less than 3.33 times, or when harvest is favored over spawning by less than 1.44 times -- the **R** model performs best (Fig. 2-4D).

The *ALV* of selecting the second-best performing model is greatest for the Late run-timing group (Table 2-3). When harvest is heavily favored (*O*:*U* ratios greater than one depicted to the right), the *ALV* from applying the second-best model can be up to 62% greater than the cost from using the best model. With symmetric loss functions (*O*:*U* = 1), the *ALV* of the second best model is 25%, and the cost declines to 4% when spawning is heavily favored (*O*:*U* ratios less than one depicted to the left).

Discussion

Results of this asymmetric loss analysis show that selection of the most appropriate model based on quantitative performance measures can be strongly affected by how managers value competing objectives. Thus, I support past recommendations that fisheries scientists and managers should consider asymmetric loss functions in the course of their analyses and decision making, respectively (Peterman 1990, Reckhow 1994, Frederick and Peterman 1995, Walters and Martell 2004). The effect of asymmetric losses varied among the run-timing groups of Fraser River sockeye salmon. In the Summer run-timing group, asymmetric loss had no impact on model selection. However, in the other three run groups, model performance was sensitive to changes in the shape of the asymmetric loss functions. Therefore, management objectives may be insufficiently reflected by failing to consider asymmetric losses that reflect comparative disadvantages of deviations from target escapements and catches.

The degree of preference for achieving spawning or harvest objectives that is necessary to affect model selection was quite variable across run-timing groups. For example, in the Early Stuart run-timing group preferring harvest objectives by only 1.18 times as much as spawning objectives resulted in an alternative model selection, while in another run-timing group (Early Summer), one objective must be preferred by at least 1.48 times over the other to cause an alternative model selection, and in the Summer run-timing group none of the asymmetries examined caused alternative model selection. The more asymmetric a loss function is, the more likely it is to have an effect on model selection.

Certain situations are more likely to be associated with highly asymmetric loss functions. For example, the loss function will be highly asymmetric where populations are extremely rare (e.g., listed as threatened or endangered or near to reaching such listing thresholds) and are subject to harvest. In such cases, there are high costs associated with failing to achieve spawning objectives. In situations which suggest the use of highly asymmetric loss functions, model selection based on standard symmetric performance measures should not be used unless decision makers explicitly acknowledge that a symmetric loss function indeed reflects their management objectives.

Costs varied for selecting a model other than the model recommended by an asymmetric loss function. In some cases, very little is lost by selecting the second-best model, but in other cases within the range of asymmetric loss functions considered here, the additional costs (*ALV*) ranged up to 63% for the next-best model. When the benefit of selecting the top-ranked model is small, managers might want to evaluate whether the effort in terms time spent in meetings to develop asymmetric loss functions is worth the potential benefit of doing so. That is, they should do an informal opportunity cost analysis to compare the cost of determining the appropriate asymmetric loss function versus the benefits of doing so. For Fraser River sockeye salmon, based on the *ALV*s from this analysis, it appears there could be considerable benefits of selecting models based on the asymmetric loss functions of managers. Conversely, if managers have a particular reason not considered here for selecting a second-best model instead of the best one, the *ALV* results can be used to determine the cost of that decision compared to using the best model over the range of asymmetric loss functions.

An additional reason to consider developing asymmetric loss functions is that the greater the asymmetry is, the greater the impact on an individual model's performance. In the Early Stuart run-timing group, applying the historic model (the best one based on a symmetric loss function analysis) could have major consequences if the actual loss function should have been asymmetric but was assumed to be symmetric. For example, applying the historic model without examining the management objectives and determining the asymmetric loss function for the management of that run-timing group could result in the perceived performance of the historic model being anywhere from best to worst among the suite of models. Thus, failing to consider the probable asymmetry of the loss associated with forecast error could potentially result in a manager choosing an inappropriate model for the management of a fish stock, thus reducing the chances of reaching spawning and harvest targets.

Further Studies

Further research could expand upon this analysis with more complex loss functions. Loss functions can take any form, not just the linear symmetric and asymmetric forms evaluated here. For example, the preferences of individuals may be best represented by loss functions that are non-linear or contain tolerance zones in which forecast errors are not associated with any loss (Lawrence and O'Connor 2005). In such a case, Fraser River sockeye salmon fisheries managers might not attribute any loss to errors that are reasonably small, and would only be concerned when errors are large enough to garner attention or cause a large deviation from harvest expectations or spawning requirements that managers deem necessary to estimate and take into account. In this case, a loss function that prescribes no cost to small errors and large costs to large errors would be more appropriate. This could be achieved by adding a threshold point to the loss function, or using a logistic-type cost function. Other possible loss functions could include costs that increase exponentially with larger errors or reach infinity if a stock goes extinct. Model evaluations with these different loss function shapes could produce different model rankings from those shown here.

The loss associated with the range of asymmetric loss values in this analysis was intended to reflect the complex multi-attribute valuation process inherent in managers' selection of a management adjustment that includes many aspects of decision-making, such as political pressure, societal norms, or cultural values. Alternatively, in conjunction with an economic analysis of the Fraser River sockeye salmon fisheries, the use of asymmetric loss functions could provide an economic value for forecast errors associated using a particular MA model.

In addition, managers may be interested in comparing the performance of more than the two top-ranked models. Appendix 4 provides the cost of the forecast error for each model for all the asymmetric losses considered, and a comparison of that model's cost with the cost of the best performing model using each asymmetric loss function.

Recommendations

Managers may want to consider a MA model selection process that involves asymmetric loss functions, given the sensitivity of model choice to the weighting of raw errors. Under current practices, failure to develop management objectives in terms of asymmetric loss could result in inappropriate model selection and management actions. The differences among run-timing groups suggest the need to develop asymmetric loss functions specific to each group. For example, due to the current conservation concerns associated with the Early Stuart run-timing group (David Patterson, pers. comm.), it is reasonable to assume that decision makers are likely to favor spawning more heavily than harvest in the management of this stock. Based upon this assumption, decision makers would have an *O*:*U* ratio of less than one, causing them to minimize the cost of forecast error through the selection of the best model in that region, the historic model. Different conditions specific to other run-timing groups may affect parameters of their asymmetric loss functions.

The Early Summer run-timing group is an aggregate group made up of many smaller stocks. The mixing of these stocks causes harvest to primarily occur on the run-timing group as an aggregate. Harvesting a stock aggregate can have detrimental affects on the weaker stocks in the aggregate, which would limit the ability to harvest the aggregate as a whole due to the concerns associated with the weak stocks. In these situations, managers may favor spawning objectives in order to avoid depleting weak stocks and ensure continued fishing on the aggregate stock. Therefore, for aggregate stocks, managers may particularly favor spawning objectives in years typically associated with high in-river loss, such as high Fraser River temperatures and flows, in order to avoid depleting weaker stocks, which would constrain aggregate harvest while weaker stocks recover. As a result, managers may wish to select the historic model for the Early Summer run-timing group so that in general the aggregate stock is more likely to exceed spawning objectives, providing a surplus that may help the population persist through extremely unfavorable years.

Recovery efforts for some stocks of the Late run-timing group, and concerns associated with changes in Late run sockeye salmon migration behavior, indicate that managers probably favor meeting or exceeding spawning objectives for this run-timing group. Based on this assumption, managers would be likely to select the run-timing model because it performs best when spawning is favored and even when harvest is slightly preferred. However, because of the large overall abundance of this run-timing group, if recovery efforts for the small populations are successful, it is possible managers would change their preferences to strongly favor harvest objectives, which would cause the discharge model to perform best based on those preferences.

The Summer run of Fraser River sockeye salmon is abundant, which results in strong pressure to harvest this more abundant group. However, the asymmetric loss function analysis showed no reason to change the choice of management adjustment model from the case of the symmetric loss function for which the T+Q model was best. Therefore, using the performance measures from Chapter 1 assuming symmetric loss should be sufficient for selecting a MA model for the Summer run-timing group. However, the results from Chapter 1 showed that even without considering the impact of asymmetric loss on model selection, based upon the variability in model rank among the management objectives represented by the five performance measures in Chapter 1, there is not an obvious choice for best model. Therefore, in addition to the well-recognized trade-offs among competing management objectives such as spawning escapement and harvest, managers should also take into account the factors that indicate good or bad model performance in general, such as the size of a model's bias, the frequency of large forecast errors, or other measures.

Both management objectives and management preferences for one objective over another affect model selection. Therefore, managers should identify their primary management concerns and then develop both appropriate performance measures and loss functions to enable them to properly identify the best models for their system, and thus increase the chances of meeting their management objectives.

Reference List

Adkison, M. D. 2009. Drawbacks of complex models in frequentist and Bayesian approaches to natural-resource management. Ecological Applications **19**:198-205.

Burnham, K. P. and D. R. Anderson. 2002. Model Selection and Multimodel Inference. Second edition. Springer-Verlag, New York.

Christoffersen, P. F. and F. X. Diebold. 1996. Further results on forecasting and model selection under asymmetric loss. Journal of Applied Econometrics **11**:561-571.

Christoffersen, P. F. and F. X. Diebold. 1997. Optimal prediction under asymmetric loss. Econometric Theory **13**:808-817.

Cooke, S. J., S. G. Hinch, G. T. Crossin, D. A. Patterson, K. K. English, M. C. Healey, J. M. Shrimpton, G. Van Der Kraak, and A. P. Farrell. 2006. Mechanistic basis of individual mortality in pacific salmon during spawning migrations. Ecology **87**:1575-1586.

Cooke, S. J., S. G. Hinch, A. P. Farrell, M. F. Lapointe, S. R. M. Jones, J. S. Macdonald, D. A. Patterson, M. C. Healey, and G. Van Der Kraak. 2004. Abnormal migration timing and high en route mortality of sockeye salmon in the Fraser River, British Columbia. Fisheries **29**:22-33.

Crossin, G. T., S. G. Hinch, S. J. Cooke, D. W. Welch, D. A. Patterson, S. R. M. Jones, A. G. Lotto, R. A. Leggatt, M. T. Mathes, J. M. Shrimpton, G. Van der Kraak, and A. P. Farrell. 2008. Exposure to high temperature influences the behaviour, physiology, and survival of sockeye salmon during spawning migration. Canadian Journal of Zoology-Revue Canadienne De Zoologie **86**:127-140.

Elliott, G. and A. Timmermann. 2008. Economic forecasting. Journal of Economic Literature **46**:3-56.

Frederick, S. W. and R. M. Peterman. 1995. Choosing fisheries harvest policies - when does uncertainty matter. Canadian Journal of Fisheries and Aquatic Sciences **52**:291-306.

Goodwin, P. 2005. Providing support for decisions based on time series information under conditions of asymmetric loss. European Journal of Operational Research **163**:388-402.

Granger, C. W. J. 1969. Prediction with a generalized cost of error function. Operational Research Quarterly **20**:199-&.

Granger, C. W. J. and M. H. Pesaran. 2000. Economic and statistical measures of forecast accuracy. Pages 537-560. John Wiley & Sons Ltd.

Hague, M. J. and D. A. Patterson. 2007. Quantifying the sensitivity of Fraser River sockeye salmon (*Oncorhynchus nerka*) management adjustment models to uncertainties in run timing, run shape and run profile. Canadian Technical Report of Fishieries and Aquatic Sciences **2776**:p.

Knetsch, J. L. 1990. Environmental-policy implications of disparities between willingness to pay and compensation demanded measures of values. Journal of Environmental Economics and Management **18**:227-237.

Knetsch, J. L. 1995a. Assumptions, behavioral findings, and policy analysis. Journal of Policy Analysis and Management **14**:68-78.

Knetsch, J. L. 1995b. Asymmetric valuation of gains and losses and preference order assumptions. Economic Inquiry **33**:134-141.

Knetsch, J. L. 2007. Biased valuations, damage assessments, and policy choices: The choice of measure matters. Ecological Economics **63**:684-689.

Knetsch, J. L. and J. A. Sinden. 1984. Willingness to pay and compensation demanded - experimental-evidence of an unexpected disparity in measures of value. Quarterly Journal of Economics **99**:507-521.

Lawrence, M. and M. O'Connor. 2005. Judgmental forecasting in the presence of loss functions. International Journal of Forecasting **21**:3-14.

Macdonald, J. S. 2000. Mortality during the migration of Fraser River sockeye salmon (*Oncorhynchus nerka*) : A study of the effect of ocean and river environmental conditions in 1997. Canadain Technical Report of Fisheries and Aquatic Sciences **2315**:120 p.

Macdonald, J. S., M. G. G. Foreman, T. Farrell, I. V. Williams, J. grout, A. Cass, J. C. Woodey, H. Enzenhofer, W. C. Clarke, R. Houtman, E. M. Donaldson, and D. Barnes. 2000. The influence of extreme water temperatures on migrating Fraser River sockeye salmon (*Oncorhynchus nerka*) during the 1998 spawning season. Canadian Technical Report of Fisheries and Aquatic Sciences **2326**:117 p.

Macdonald, J. S., D. A. Patterson, M. J. Hague, and I. C. Guthrie. 2009. Improving the sustainability of sockeye salmon fisheries by modeling the influence of environmental factors on spawning migration success.

Patterson, D. A., J. S. Macdonald, K. M. Skibo, D. P. Barnes, I. Guthrie, and J. Hills. 2007a. Reconstructing the summer thermal history for the lower Fraser River, 1941 to 2006, and implications for adult sockeye salmon (*Oncorhynchus nerka*) spawning migration.

Patterson, D. A., K. M. Skibo, D. P. Barnes, J. A. Hills, and J. S. Macdonald. 2007b. The influence of water temperature on time to surface for adult sockeye salmon carcasses and the limitations in estimating salmon carcasses in the Fraser River, British Columbia. North American Journal of Fisheries Management **27**:878-884.

Patton, A. J. and A. Timmermann. 2007. Testing forecast optimality under unknown loss. Journal of the American Statistical Association **102**:1172-1184.

Peterman, R. M. 1990. Statistical power analysis can improve fisheries research and management. Canadian Journal of Fisheries and Aquatic Sciences **47**:2-15.

Rand, P. S., S. G. Hinch, J. Morrison, M. G. G. Foreman, M. J. MacNutt, J. S. Macdonald, M. C. Healey, A. P. Farrell, and D. A. Higgs. 2006. Effects of river discharge, temperature, and future climates on energetics and mortality of adult migrating Fraser River sockeye salmon. Transactions of the American Fisheries Society **135**:655-667.

Reckhow, K. H. 1994. Importance of scientific uncertainty in decision-making. Environmental Management **18**:161-166.

Shepard, M. P. and A. W. Argue. 2005. The 1985 Pacific Salmon Treaty: sharing conservation burdens and benefits. UBC Press, Vancouver.

Walters, C. J. and S. Martell. 2004. Fisheries Ecology and Management. Princeton University Press, Princeton.

Xie, L. S. and W. W. Hsieh. 1989. Predicting the return migration routes of the Fraser-River sockeye salmon (*Oncorhynchus-nerka*). Canadian Journal of Fisheries and Aquatic Sciences **46**:1287-1292.

Xie, Y. B. 2000. A range-dependent echo-association algorithm and its application in split-beam sonar tracking of migratory salmon in the Fraser River watershed. Ieee Journal of Oceanic Engineering **25**:387-398.

Zar, J. H. 1996. Biostatistical Analysis. 3rd Ed. edition. Prentice Hall, Inc., Upper Saddle River, New Jersey.

Zellner, A. 1986. Bayesian-estimation and prediction using asymmetric loss functions. Journal of the American Statistical Association **81**:446-451.

Table 2-1. Example of management adjustment (MA) data and forecast error calculations. The first row contains a hypothetical example of actual abundances (in thousands of fish) and calculated variables used to evaluate the model forecasts. Each year the potential spawning escapement (*PSE*) is calculated by subtracting the forecasted in-river catch (C) from the abundance estimate obtained at the Mission sampling location (M). Later in the season, the in-river loss is calculated by subtracting the actual observed spawning escapement (*SE*) from the *PSE* and the difference between estimates (DBE) is calculated by taking the natural log of *SE* divided by *PSE*. The middle two rows contain two hypothetical examples of model forecasts and their outcomes. Models forecast a DBE each year that is used to produce the forecasted SE/PSE and a forecasted SE based on the predicted *PSE*. Model forecasts are evaluated by subtracting the observed *SE*/*PSE* from the forecasted *SE*/*PSE* to produce the raw error (*RE*), and by comparing the outcome of the model forecast to the actual in-river loss and the latter actual loss is the ideal management adjustment. Finally, these calculations assume both (1) that the management adjustment applied to the fisheries is the same as the forecasted management adjustment, and (2) that the error in terms of achieving the spawning escapement target is equivalent to the difference between the spawner abundance from the MA forecast and the actual spawner abundance, the forecasted spawner abundance is compared to the spawning escapement target. The last two rows contain examples of components used to determine the lost value (*LV*) and additional lost value (*ALV*) of the same two hypothetical model forecasts based on hypothetical managers' preferences (Fig 2-2 has additional information). *LV* is the product of the raw error and the slope of the appropriate limb of the loss function (O for overestimates and U for underestimates). The additional lost value compared to the best model is the lost value of a given model minus the lost value of the best model divided by the latter, i.e., lost value of the best model, expressed as a percentage.

Table 2-1

	Potential spawning escapement (*PSE*)	Mission total abundance estimate (M)	Forecasted in-river catch (C)	Actual Spawning escapement (*SE*)	In-river loss (*PSE-SE*)	Difference Between Estimates (DBE) Ln(*SE*/*PSE*)	Observed *SE*/*PSE*
Actual	400	500	100	350	50	-0.134	0.875

	Forecasted DBE Ln(*SE*/*PSE*)	*Forecasted SE*/*PSE*	Raw Error (*RE*)	Forecasted SE (if *PSE* = 400)	Estimate of in-river loss by MA model	Management Adjustment estimated by MA model	Actual spawners compared to spawning escapement target*
Forecast (Model 1)	-0.078	0.925	0.05	370	30 (an underestimate)	Too small	Below target
Forecast (Model 2)	-0.192	0.825	-0.05	330	70 (an overestimate)	Too big	Above target

	Raw Error (*RE*)	slope (*O*)	slope (*U*)	*O*:*U* ratio	Manager or user preference	Lost Value (*LV*)	Additional Lost Value (ALV)	Estimate of in-river loss by MA model	Harvest	Spawners
Forecast (Model 1)	0.05	1.25	1	1.25	Harvest	0.05	25%	Underestimate (slope = *U*)	Too many harvested	Below target
Forecast (Model 2)	-0.05	0.8	1	0.8	Spawning	0.04	0	Overestimate (slope = *O*)	Reduced too much	Above target

* Outcome based on two simplifying assumptions; one, that the management adjustment applied to the fisheries is the same as the forecasted management adjustment, and two, the error in terms of achieving the spawning escapement target is equivalent to the difference between the spawner abundance from the management adjustment forecast and the actual spawner abundance.

Table 2-2. Management Adjustment models. T is the 31-day symmetric average river temperature measured at Qualark (^oC) in the lower Fraser River symmetrically centered on the Hells Gate 50% date (i.e., the date at which 50% of the run has migrated past Hells Gate). Q is the 31-day symmetric average discharge measured at Hope (m^3/s) symmetrically centered on Hells Gate 50% date. D_{50} is the date when 50% of a run has passed Hells Gate. H is the historical average DBE (the historical difference between estimates of upriver spawning escapement abundance and lower-river potential spawning escapement abundance estimates), n is calendar year, and the a and b parameters are the best-fit regression parameters that result from fitting each of the models in each year of the retrospective analysis. The symbol for each model is used as an abbreviation for the full model name within the text.

Table 2-2

Equation	Symbol	Model Variables (Model Name)	Equation
1	**T**	Temperature (Temperature)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1 T + b_2 T^2$
2	**Q**	Discharge (Discharge)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1 Q + b_2 Q^2$
3	**T+Q**	Temperature-plus-discharge (Temperature-plus-discharge)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1 T + b_2 T^2 + b_3 Q + b_4 Q^2$
4	**R**	Run-timing date (Run-timing)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1 D_{50}$
5	**H**	Average historical DBE (Historic)	$\ln\left(\frac{SE}{PSE}\right) = a + b_1 H$ $H = \frac{\sum_{n=1977}^{N} observed \ln(SE/PSE)_n}{N}$
6	**NMA**	None (No Management Adjustment)	$\ln\left(\frac{SE}{PSE}\right) = 0$

Table 2-3. For each of the four run-timing groups, the first row is the additional lost value (*ALV*) of selecting the second-best model as a percent of the best model's cost, conditional upon the cost of overestimates (*O*) and underestimates (*U*) of in-river loss, which are associated with overescapement and underescapement, respectively. Shading corresponds to the top-performing model (not the second-best model listed in rows below) for each *O* and *U* combination: Historic model = , Temperature model = , Discharge model = , Temperature-plus-discharge model = , Run-timing model = . The second row for each run-timing group displays the second-best performing model for that *O* and *U* combination. Model labels are: **T** = Temperature, **Q** = Discharge, **T+Q** = Temperature-plus-discharge, **R** = Run-timing, **H** = Historic, **NMA** = No management adjustment model.

Spawning favoured ← *O:U* → Harvest favoured

Run-timing group	O 0.5 U 2.0	O 0.5 U 1.8	O 0.5 U 1.6	O 0.5 U 1.4	O 0.5 U 1.2	O 0.5 U 1.0	O 0.6 U 1.0	O 0.7 U 1.0	O 0.8 U 1.0	O 0.9 U 1.0	O 1.0 U 1.0	O 1.2 U 1.0	O 1.4 U 1.0	O 1.6 U 1.0	O 1.8 U 1.0	O 2.0 U 1.0	O 2.0 U 0.9	O 2.0 U 0.8	O 2.0 U 0.7	O 2.0 U 0.6	O 2.0 U 0.5
E. Stuart	33	31	29	26	23	19	15	12	9	6	4	0	1	1	1	1	2	2	2	2	3
	T	T	T	T	T	T	T	T	T	T	T	H	T	R	R	R	R	R	R	R	R
E. Summer	30	27	24	20	15	9	4	1	5	9	12	9	6	4	2	1	1	3	5	8	6
	T+Q	T+Q	T+Q	T+Q	T+Q	T+Q	T+Q	H	H	H	T	T	T	T	T	T	T+Q	T+Q	T+Q	T+Q	NMA
Summer	15	15	15	14	14	14	13	13	13	12	12	11	11	11	10	10	9	9	9	8	8
	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T	T
Late	4	2	1	4	8	13	17	21	24	27	25	12	2	7	15	23	32	42	55	62	54
	R	R	H	H	H	H	H	H	H	H	Q	Q	Q	R	R	R	R	R	R	NMA	NMA
	0.25					**0.5**					**1**					**2**					**4**

O:*U* ratio

Figure 2-1. Fraser River map showing data collection points and spawning locations. Dates in the legend are the historic median Hells Gate 50% run-timing dates for each run-timing group.

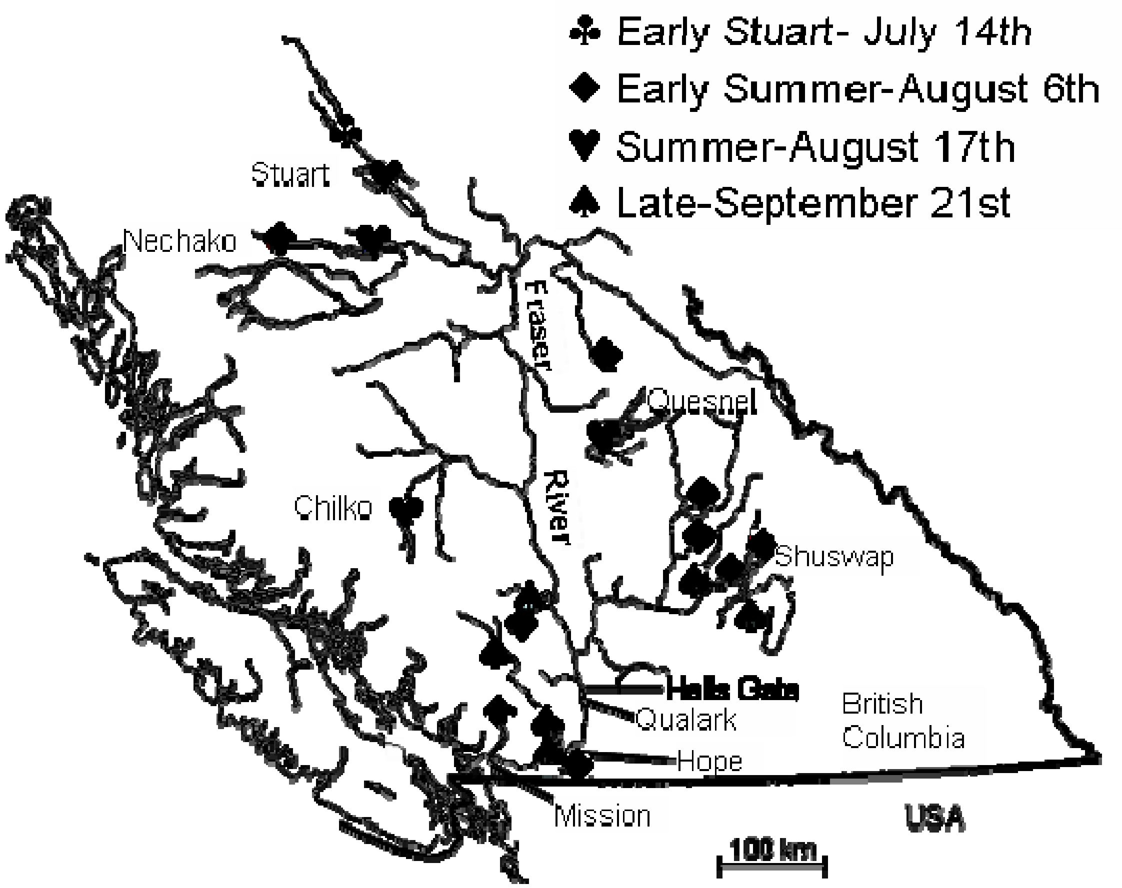


Figure 2-2. Example loss functions. (B) Symmetric loss function. Equal lost value (LV) results from both overestimates and underestimates of in-river loss of equal magnitude. That is, the perceived loss from failing to meet spawning objectives by a given amount equals the loss from failing to meet harvest objectives by the same amount. (A) Asymmetric loss function, case A; $O = 2$, $U = 0.5$, ratio O:$U = 4$. Overestimates of in-river loss are 4 times as undesirable as underestimates of in-river loss. That is, harvest is favored because the perceived loss from failing to meet harvest objectives is four times as large as the perceived loss from failing to meet spawning objectives. (C) Asymmetric loss function, case C, $O = 0.5$, $U = 2$, ratio O:$U = 0.25$. Overestimates of in-river loss are 0.25 times as undesirable as underestimates of in-river loss. That is, spawning is favored because the perceived loss from failing to meet spawning objectives by a given amount is four times as large as the perceived loss from failing to meet harvest objectives by that same amount.

Fig. 2-2

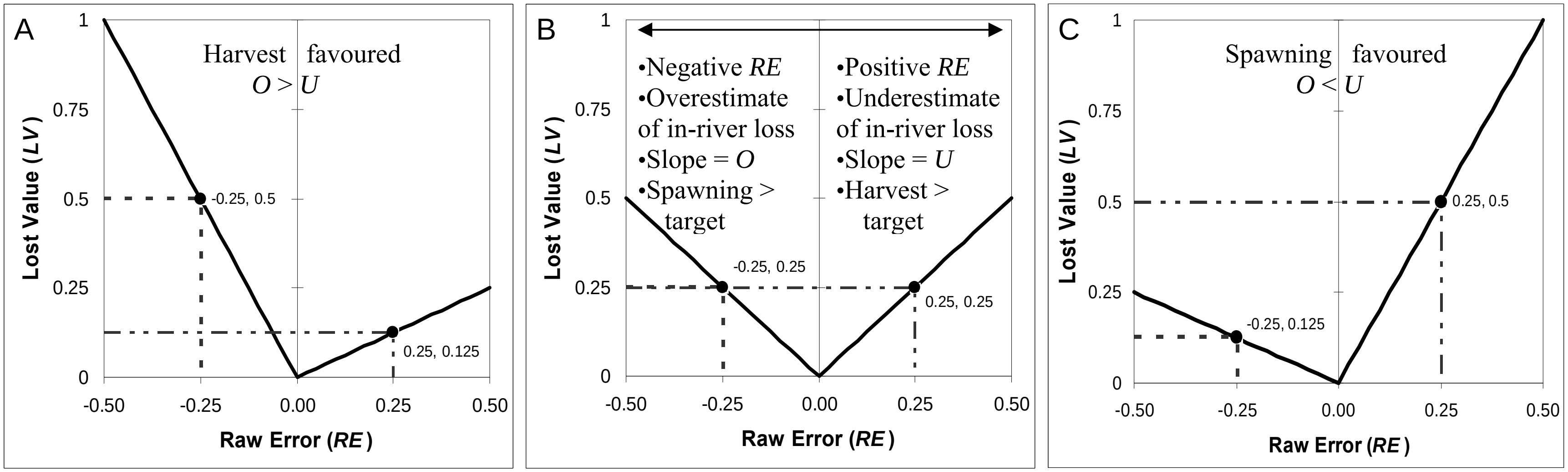

A
Harvest favoured
O > U
-0.25, 0.5
0.25, 0.125
Lost Value (LV)
Raw Error (RE)
1
0.75
0.5
0.25
0
-0.50
-0.25
0.00
0.25
0.50
B
•Negative RE
•Overestimate of in-river loss
•Slope = O
•Spawning > target
•Positive RE
•Underestimate of in-river loss
•Slope = U
•Harvest > target
-0.25, 0.25
0.25, 0.25
Lost Value (LV)
Raw Error (RE)
C
Spawning favoured
O < U
0.25, 0.5
-0.25, 0.125
Lost Value (LV)
Raw Error (RE)

Figure 2-3. Characteristics of the loss functions produced by the cost of overestimating in-river loss (*O*) i.e., a negative *RE*, and the cost of underestimating in-river loss (*U*), i.e., positive *RE*. An *O*:*U* ratio of 1 produces a symmetric loss function representing cases in which managers are indifferent between (no preference for) spawning and harvest objectives. The further to the right of the *O*:*U* ratio of 1, the greater the cost of overestimating in-river loss of adult sockeye salmon relative to underestimating it and the more managers prefer to meet harvest objectives rather than spawning objectives. The further to the left of the *O*:*U* ratio of 1, the greater the cost of underestimates relative to overestimates and the more managers prefer to meet spawning objectives rather than harvest objectives.

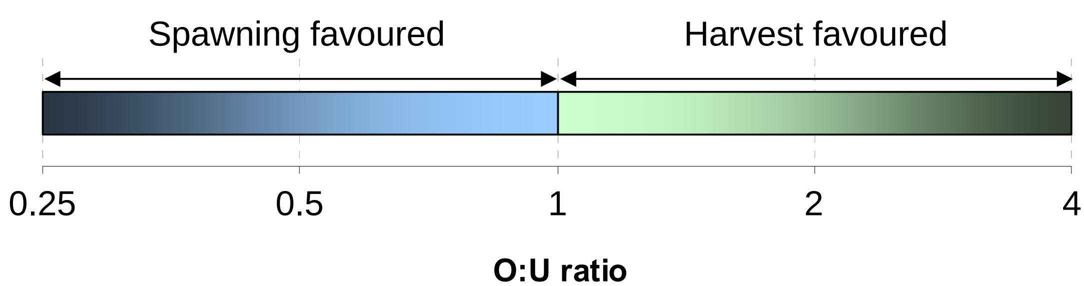
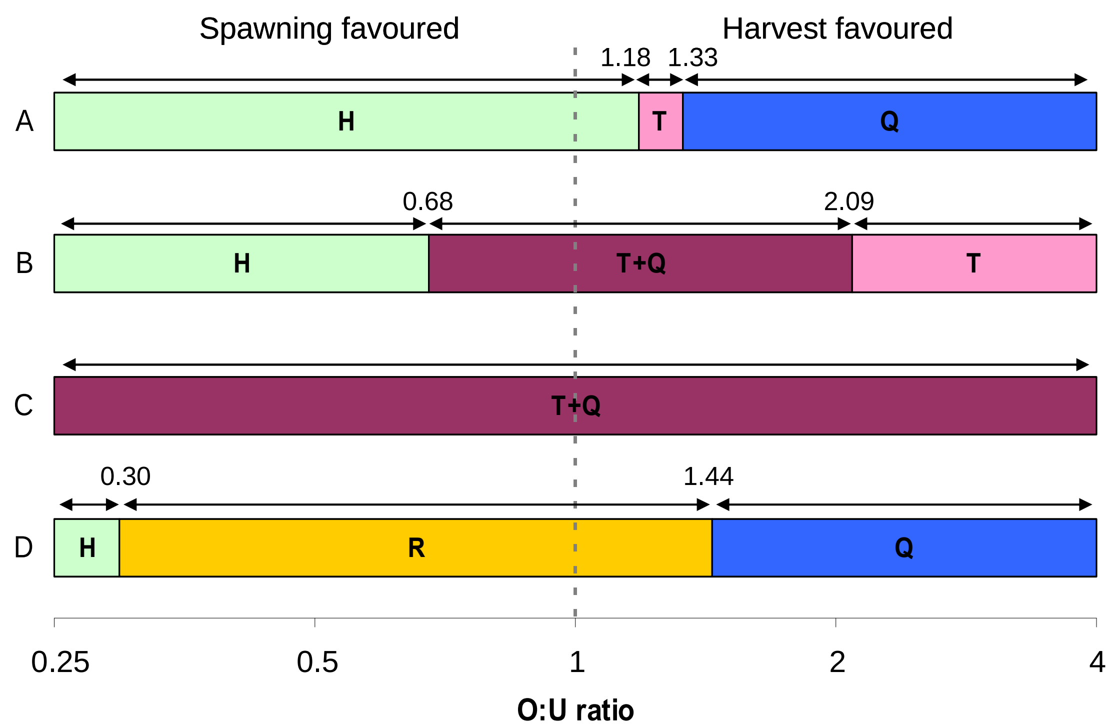


Figure 2-4. For each of the four run-timing groups of Fraser River sockeye salmon, the optimal model conditioned on the ratio of the cost of overestimates (*O*) and underestimates (*U*) of in-river loss (*O*:*U*). O:U ratios less than 1.0 indicate spawning objectives are favored and O:U ratios of greater than 1.0 indicate harvest is favored. Each shaded area is labeled with the model that performs best for the asymmetric loss function created by that O:U ratio. Model labels are: **T** = Temperature, **Q** = Discharge, **T+Q** = Temperature-plus-discharge, **R** = Run-timing, **H** = Historic. Run-timing group labels are: A = Early Stuart, B = Early Summer, C = Summer, D = Late.



APPENDICES

Appendix 1: Yearly Results

I calculated the yearly model error to show which model would have performed best in each year of the retrospective evaluation, thereby providing a means to compare management results on a yearly basis with the long-term performance measures discussed previously. The following tables show the raw error (*RE*, Eq. 7) from each model in each year from 1995 to 2007 separated by run-timing group. The first table shows the raw error from the six models evaluated in the retrospective analysis while the second includes the raw error from the alternative forecasting techniques. The models with the two best forecasts in each year are highlighted.

Early Stuart	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	0.024	-0.103	0.429	0.259	-0.045	-0.213	-0.089	0.257	0.264	0.242	0.098	-0.541	0.296
Discharge	0.048	0.019	0.575	0.643	0.094	-0.157	-0.179	0.007	0.246	0.569	0.073	-0.300	0.066
Temperature + Discharge	0.054	0.180	1.084	0.132	0.127	-0.298	-0.076	0.049	0.297	0.221	0.172	-0.527	0.055
Run Timing	-0.033	0.022	0.398	0.504	0.457	0.054	-0.217	0.138	0.121	0.459	-0.143	-0.287	0.154
Historic	-0.027	0.029	0.356	0.343	0.229	-0.250	-0.442	-0.024	-0.041	0.252	-0.223	-0.467	-0.075
No MA	0.259	0.316	0.705	0.804	0.828	0.405	0.165	0.560	0.551	0.907	0.503	0.221	0.585

Early Summer	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	-0.215	0.031	0.303	0.428	0.654	-0.442	-0.083	-0.076	0.002	0.326	0.315	0.340	-0.048
Discharge	-0.490	-0.039	0.681	0.358	0.388	-0.523	-0.037	-0.039	0.007	0.360	-0.190	-0.122	-0.071
Temperature + Discharge	-0.396	0.010	0.343	0.452	0.343	-0.620	0.082	0.121	-0.062	0.328	0.025	-0.106	0.027
Run Timing	-0.417	-0.120	0.252	0.372	0.443	-0.509	-0.107	-0.134	0.096	0.522	0.240	0.204	-0.215
Historic	-0.483	-0.166	0.170	0.234	0.221	-0.686	-0.285	-0.251	-0.018	0.330	0.018	0.014	-0.394
No MA	-0.127	0.148	0.508	0.643	0.741	-0.150	0.181	0.181	0.405	0.821	0.609	0.636	0.221

Summer	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	-0.015	-0.115	0.179	0.084	0.257	-0.429	-0.088	NA	0.177	0.050	0.194	0.298	0.259
Discharge	0.121	-0.211	0.077	0.403	0.116	-0.488	-0.140	NA	0.107	0.615	0.035	-0.130	0.200
Temperature + Discharge	-0.013	-0.130	0.185	0.089	0.199	-0.432	-0.052	NA	0.148	0.055	0.144	0.122	0.346
Run Timing	0.087	-0.237	0.088	0.431	0.147	-0.555	-0.229	NA	0.238	0.720	0.382	0.242	0.066
Historic	0.105	-0.190	0.078	0.387	0.090	-0.559	-0.211	NA	0.227	0.584	0.125	0.004	-0.194
No MA	0.068	-0.246	0.020	0.393	0.139	-0.553	-0.246	NA	0.213	0.696	0.369	0.295	0.104

Late	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	NA	0.829	0.134	0.662	0.071	2.355	0.053	0.063	-0.606	-0.094	NA	-0.253	-0.193
Discharge	NA	0.736	0.490	0.540	0.056	-0.027	0.010	0.039	0.442	0.383	NA	0.153	-0.256
Temperature + Discharge	NA	NA	NA	0.770	-0.126	-0.036	0.015	-0.142	0.969	0.220	NA	0.144	-0.313
Run Timing	NA	0.736	-0.044	0.048	0.008	0.027	-0.032	-0.409	-0.532	-0.046	NA	-0.255	-0.375
Historic	NA	0.379	-0.272	-0.220	-0.114	0.108	-0.078	-0.833	-0.522	0.024	NA	-0.432	-0.257
No MA	NA	0.713	0.467	0.478	0.577	0.956	0.882	0.086	0.302	0.821	NA	0.362	0.493

best forecast   next best forecast

Early Stuart	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	0.024	-0.103	0.429	0.259	-0.045	-0.213	-0.089	0.257	0.264	0.242	0.098	-0.541	0.296
Discharge	0.048	0.019	0.575	0.643	0.094	-0.157	-0.179	0.007	0.246	0.569	0.073	-0.300	0.066
Temperature + Discharge	0.054	0.180	1.084	0.132	0.127	-0.298	-0.076	0.049	0.297	0.221	0.172	-0.527	0.055
Run Timing	-0.033	0.022	0.398	0.504	0.457	0.054	-0.217	0.138	0.121	0.459	-0.143	-0.287	0.154
Historic	-0.027	0.029	0.356	0.343	0.229	-0.250	-0.442	-0.024	-0.041	0.252	-0.223	-0.467	-0.075
No MA	0.259	0.316	0.705	0.804	0.828	0.405	0.165	0.560	0.551	0.907	0.503	0.221	0.585
AICc weights	0.047	0.124	0.471	0.446	0.255	-0.209	-0.246	0.100	0.213	0.250	0.042	-0.521	0.128
MRE optimized weights	NA	0.025	0.430	0.259	-0.045	-0.213	-0.089	-0.024	-0.041	0.252	-0.223	-0.467	-0.042
MAE optimized weights	NA	0.025	0.454	0.324	0.169	-0.219	-0.147	0.246	0.251	0.262	0.076	-0.519	0.183
RMSE optimized weights	NA	0.025	0.452	0.343	0.161	-0.226	-0.182	0.247	0.200	0.246	-0.019	-0.515	0.156

Early Summer	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	-0.215	0.031	0.303	0.428	0.654	-0.442	-0.083	-0.076	0.002	0.326	0.315	0.340	-0.048
Discharge	-0.490	-0.039	0.681	0.358	0.388	-0.523	-0.037	-0.039	0.007	0.360	-0.190	-0.122	-0.071
Temperature + Discharge	-0.396	0.010	0.343	0.452	0.343	-0.620	0.082	0.121	-0.062	0.328	0.025	-0.106	0.027
Run Timing	-0.417	-0.120	0.252	0.372	0.443	-0.509	-0.107	-0.134	0.096	0.522	0.240	0.204	-0.215
Historic	-0.483	-0.166	0.170	0.234	0.221	-0.686	-0.285	-0.251	-0.018	0.330	0.018	0.014	-0.394
No MA	-0.127	0.148	0.508	0.643	0.741	-0.150	0.181	0.181	0.405	0.821	0.609	0.636	0.221
AICc weights	-0.470	-0.153	0.214	0.286	0.272	-0.667	-0.280	-0.223	-0.010	0.346	-0.033	-0.005	-0.321
MRE optimized weights	NA	0.031	0.303	0.399	0.355	-0.681	-0.187	-0.147	-0.005	0.327	0.167	0.153	-0.268
MAE optimized weights	NA	0.031	0.303	0.398	0.586	-0.686	-0.285	0.029	-0.037	0.328	0.104	0.039	-0.084
RMSE optimized weights	NA	0.031	0.303	0.428	0.467	-0.686	-0.204	-0.165	-0.015	0.328	0.159	0.088	-0.174

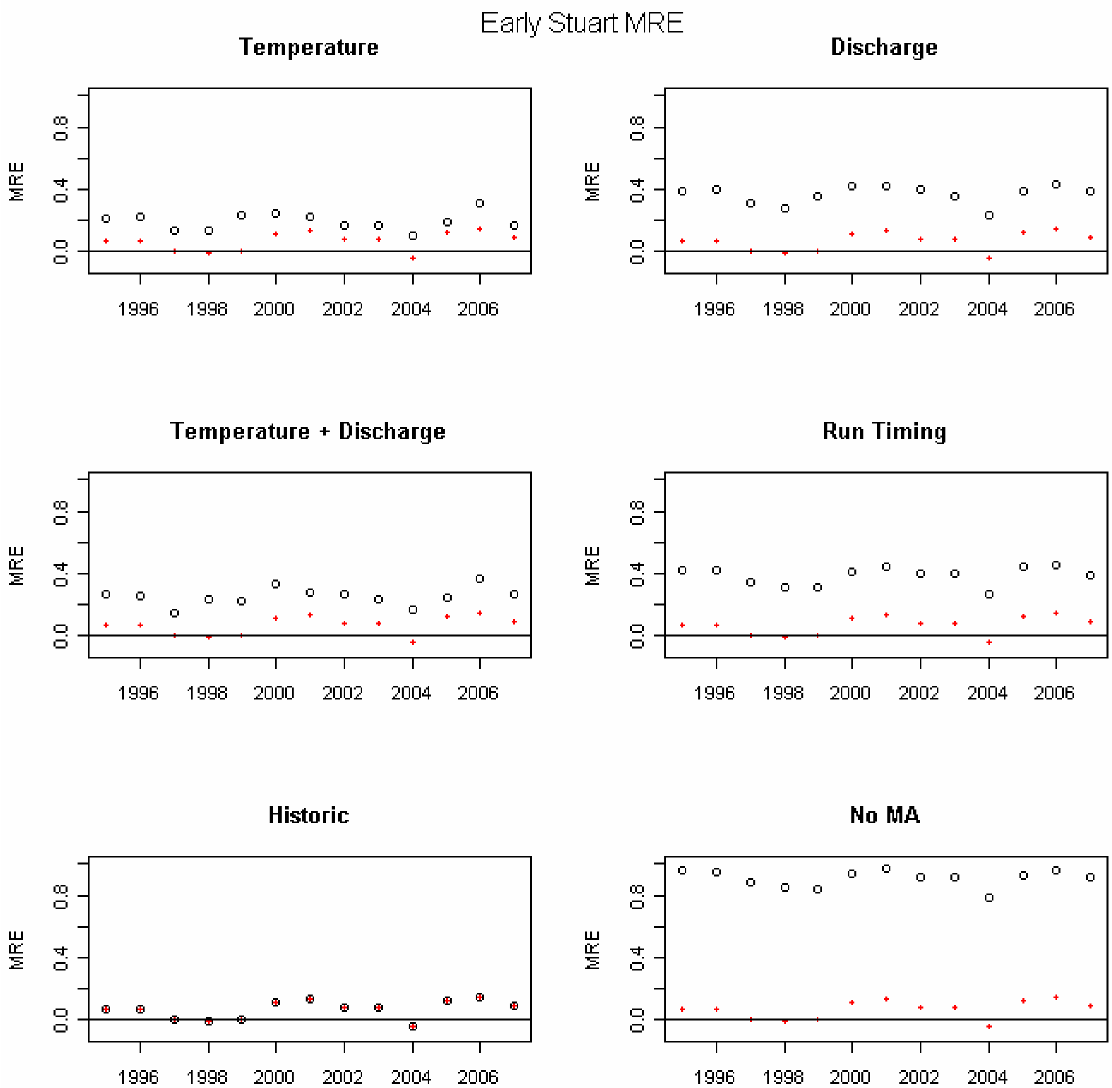
Summer	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	-0.015	-0.115	0.179	0.084	0.257	-0.429	-0.088	NA	0.177	0.050	0.194	0.298	0.259
Discharge	0.121	-0.211	0.077	0.403	0.116	-0.488	-0.140	NA	0.107	0.615	0.035	-0.130	0.200
Temperature + Discharge	-0.013	-0.130	0.185	0.089	0.199	-0.432	-0.052	NA	0.148	0.055	0.144	0.122	0.346
Run Timing	0.087	-0.237	0.088	0.431	0.147	-0.555	-0.229	NA	0.238	0.720	0.382	0.242	0.066
Historic	0.105	-0.190	0.078	0.387	0.090	-0.559	-0.211	NA	0.227	0.584	0.125	0.004	-0.194
No MA	0.068	-0.246	0.020	0.393	0.139	-0.553	-0.246	NA	0.213	0.696	0.369	0.295	0.104
AICc weights	0.077	-0.226	0.049	0.353	0.138	-0.504	-0.182	NA	0.191	0.219	0.214	0.284	0.267
MRE optimized weights	NA	-0.134	0.078	0.350	0.199	-0.432	-0.141	NA	0.107	0.490	0.194	0.122	0.346
MAE optimized weights	NA	-0.134	0.169	0.121	0.257	-0.429	-0.052	NA	0.148	0.055	0.144	0.122	0.346
RMSE optimized weights	NA	-0.134	0.179	0.197	0.257	-0.441	-0.052	NA	0.148	0.055	0.144	0.122	0.346

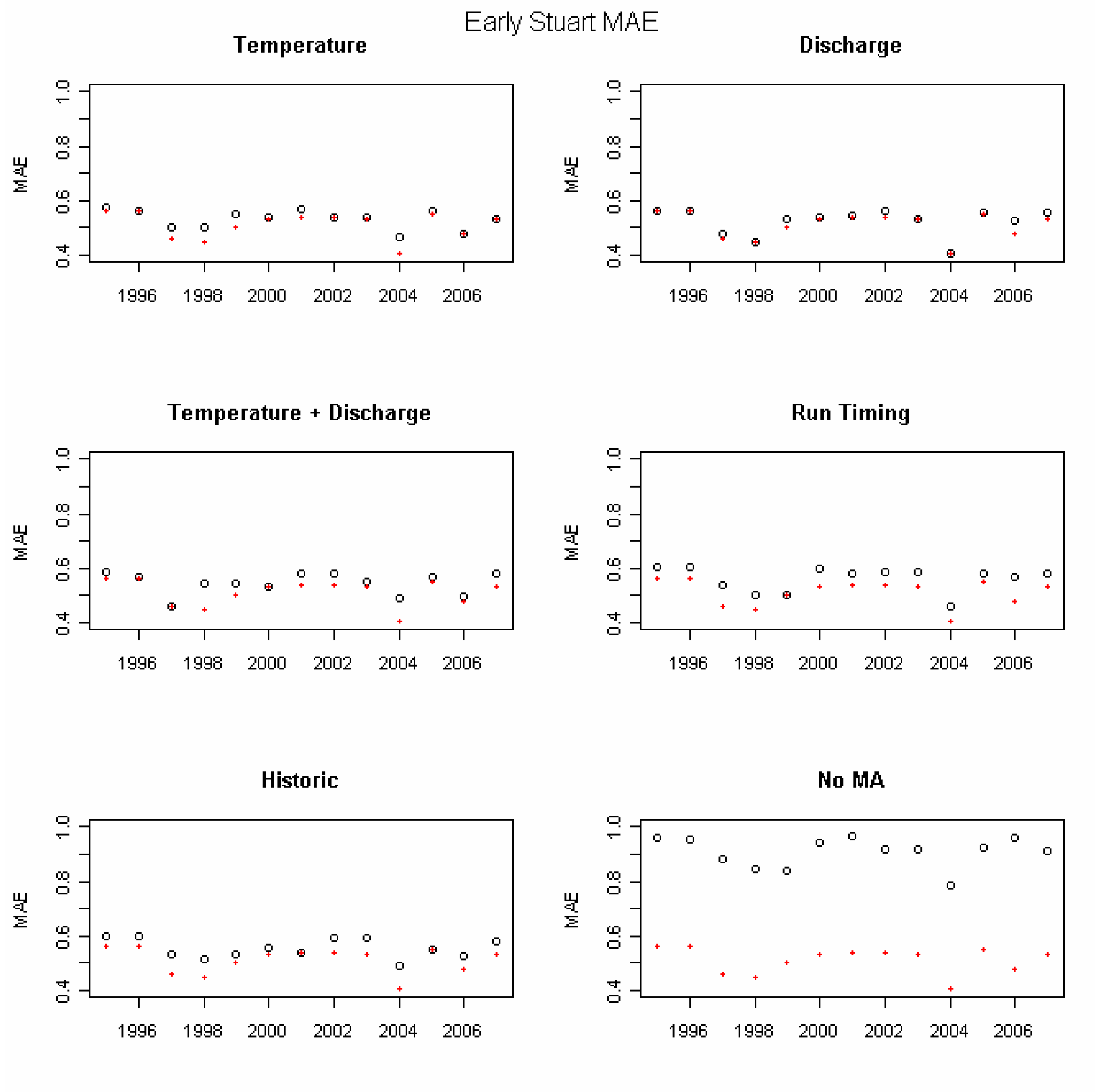
Late	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Temperature	NA	0.829	0.134	0.662	0.071	2.355	0.053	0.063	-0.606	-0.094	NA	-0.253	-0.193
Discharge	NA	0.736	0.490	0.540	0.056	-0.027	0.010	0.039	0.442	0.383	NA	0.153	-0.256
Temperature + Discharge	NA	NA	NA	0.770	-0.126	-0.036	0.015	-0.142	0.969	0.220	NA	0.144	-0.313
Run Timing	NA	0.736	-0.044	0.048	0.008	0.027	-0.032	-0.409	-0.532	-0.046	NA	-0.255	-0.375
Historic	NA	0.379	-0.272	-0.220	-0.114	0.108	-0.078	-0.833	-0.522	0.024	NA	-0.432	-0.257
No MA	NA	0.713	0.467	0.478	0.577	0.956	0.882	0.086	0.302	0.821	NA	0.362	0.493
AICc weights	NA	NA	NA	NA	-0.126	0.042	-0.033	-0.412	-0.532	-0.045	NA	-0.224	-0.367
MRE optimized weights	NA	NA	-0.272	-0.220	-0.114	0.108	-0.078	-0.831	-0.506	0.027	NA	-0.423	-0.259
MAE optimized weights	NA	NA	-0.272	-0.216	-0.114	0.108	-0.078	-0.830	-0.517	0.025	NA	-0.430	-0.258
RMSE optimized weights	NA	NA	-0.272	-0.217	-0.089	0.085	-0.062	-0.659	-0.060	0.203	NA	-0.154	-0.257

Appendix 2: Jack-knife

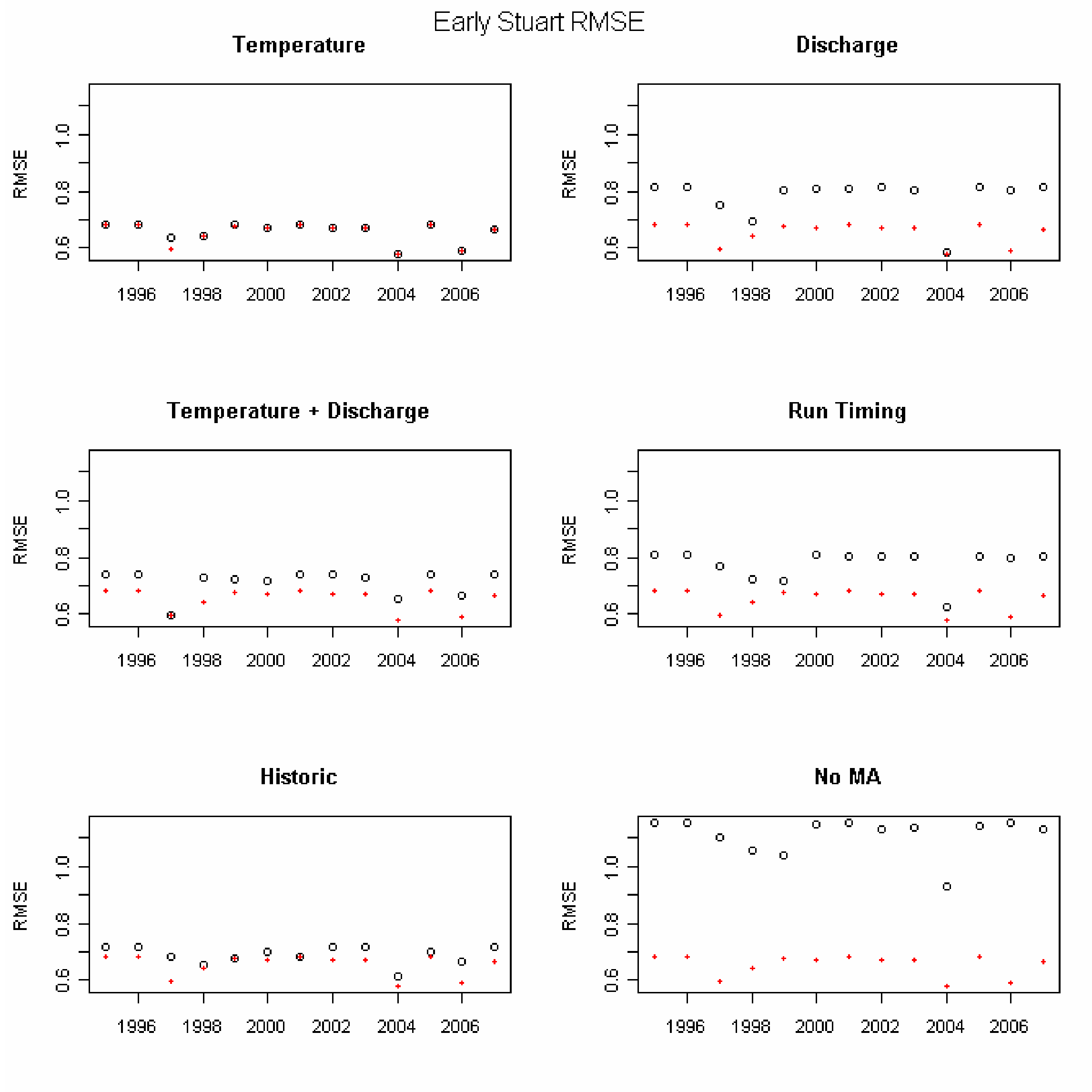
I used a jack-knife technique (Shao and Dongsheng 1995) to test the robustness of results from the retrospective analysis to the particular sequence of events/years used in my evaluation. One year of the retrospective analysis was removed at a time, the performance measure results were reassessed for each model using the remaining data, and then that data point was put back into the data set. This was repeated for all 13 years of the retrospective analysis.

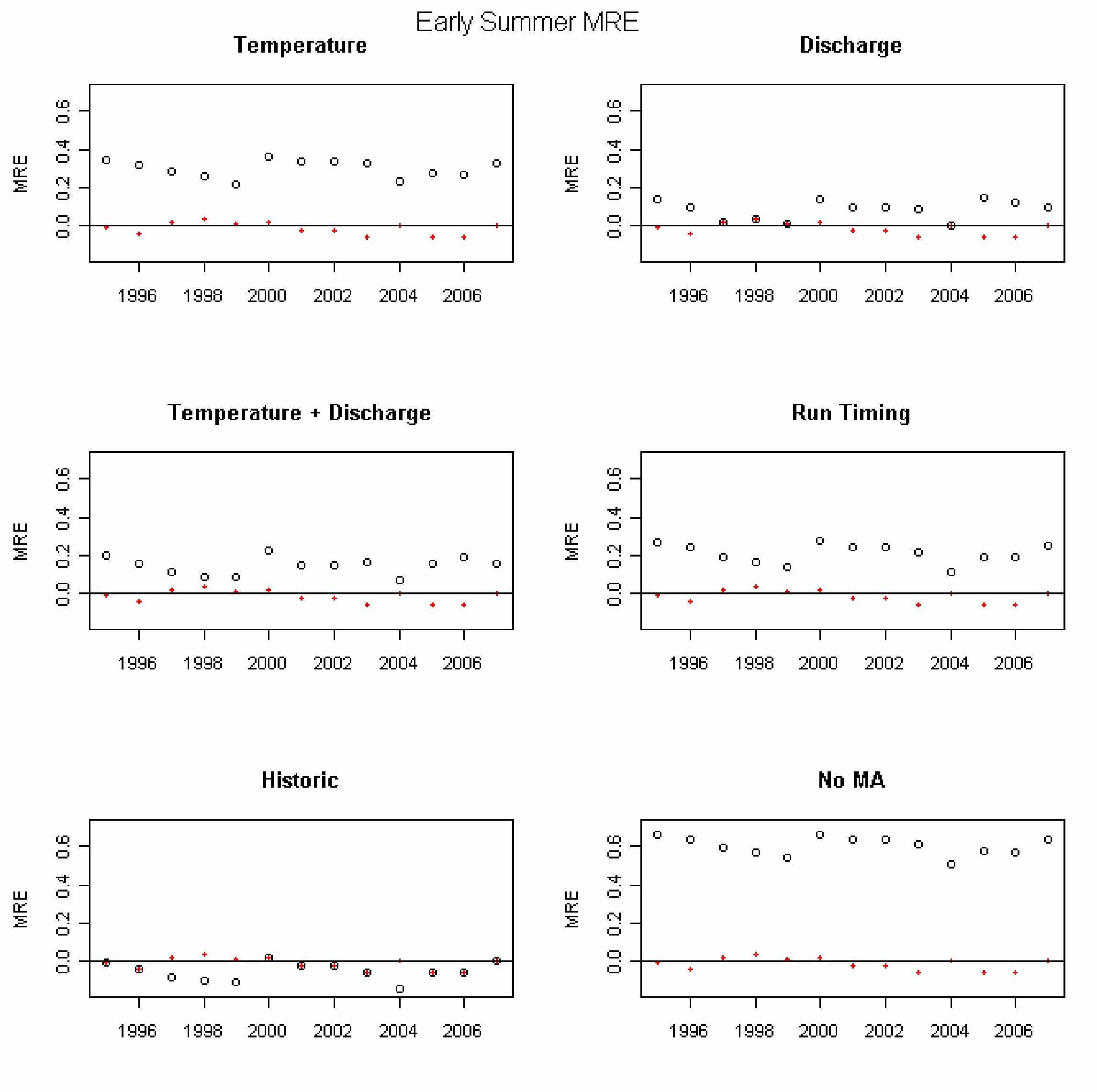
The plots below show the variability in performance measure results from year to year. The filled red circles indicate the best score for each performance measure when that year was removed from the analysis. The open black circles show results for the model being plotted. When the red circle falls inside of the black circle, that model performance was best when that year was removed from the retrospective analysis. See Chapter 1, Figure 1-4 for the model ranking for the full retrospective analysis.


Early Stuart MRE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MRE
0.0
0.4
0.8
1996
1998
2000
2002
2004
2006

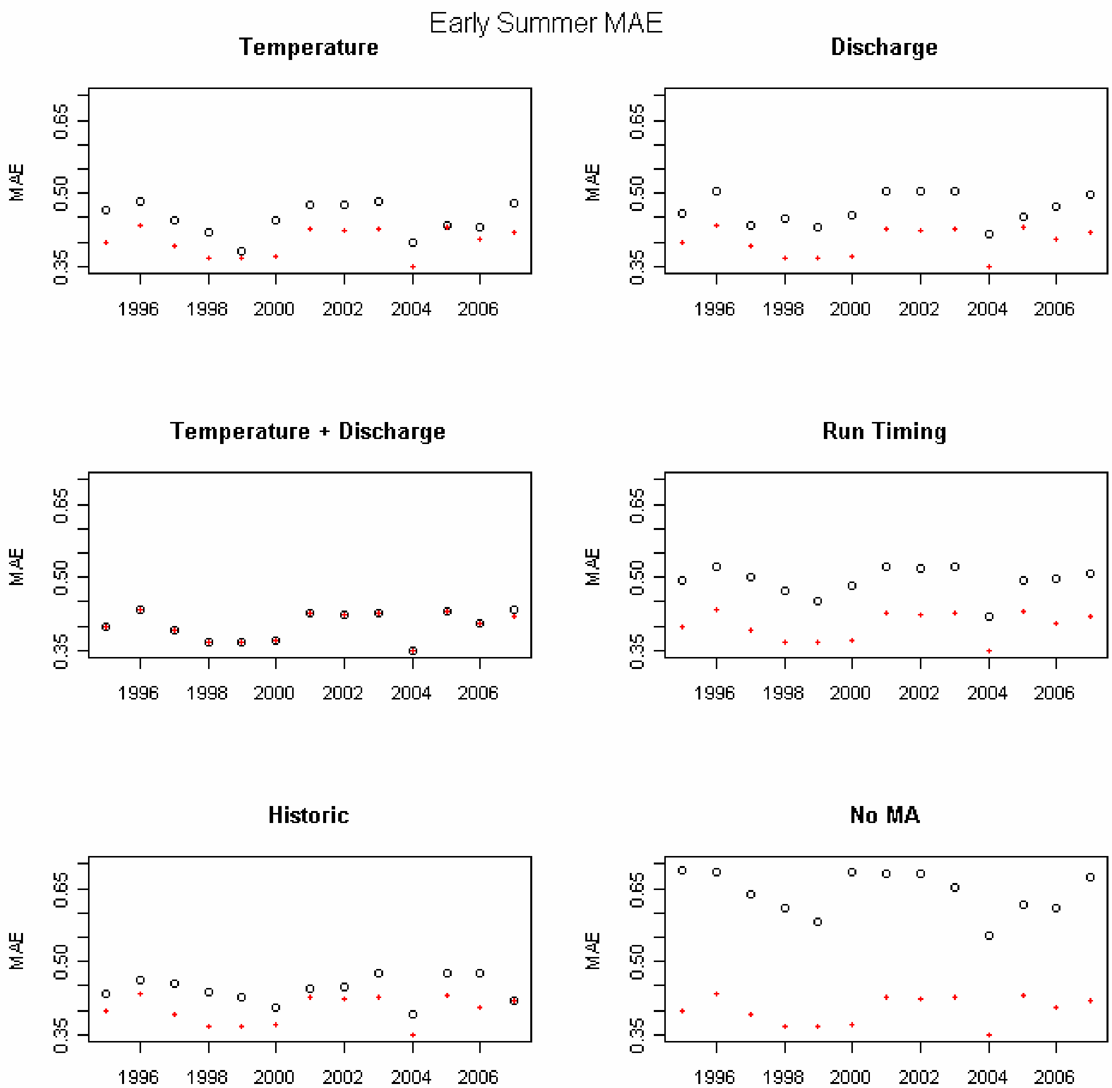


Early Stuart MAE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MAE
0.4
0.6
0.8
1.0
1996
1998
2000
2002
2004
2006

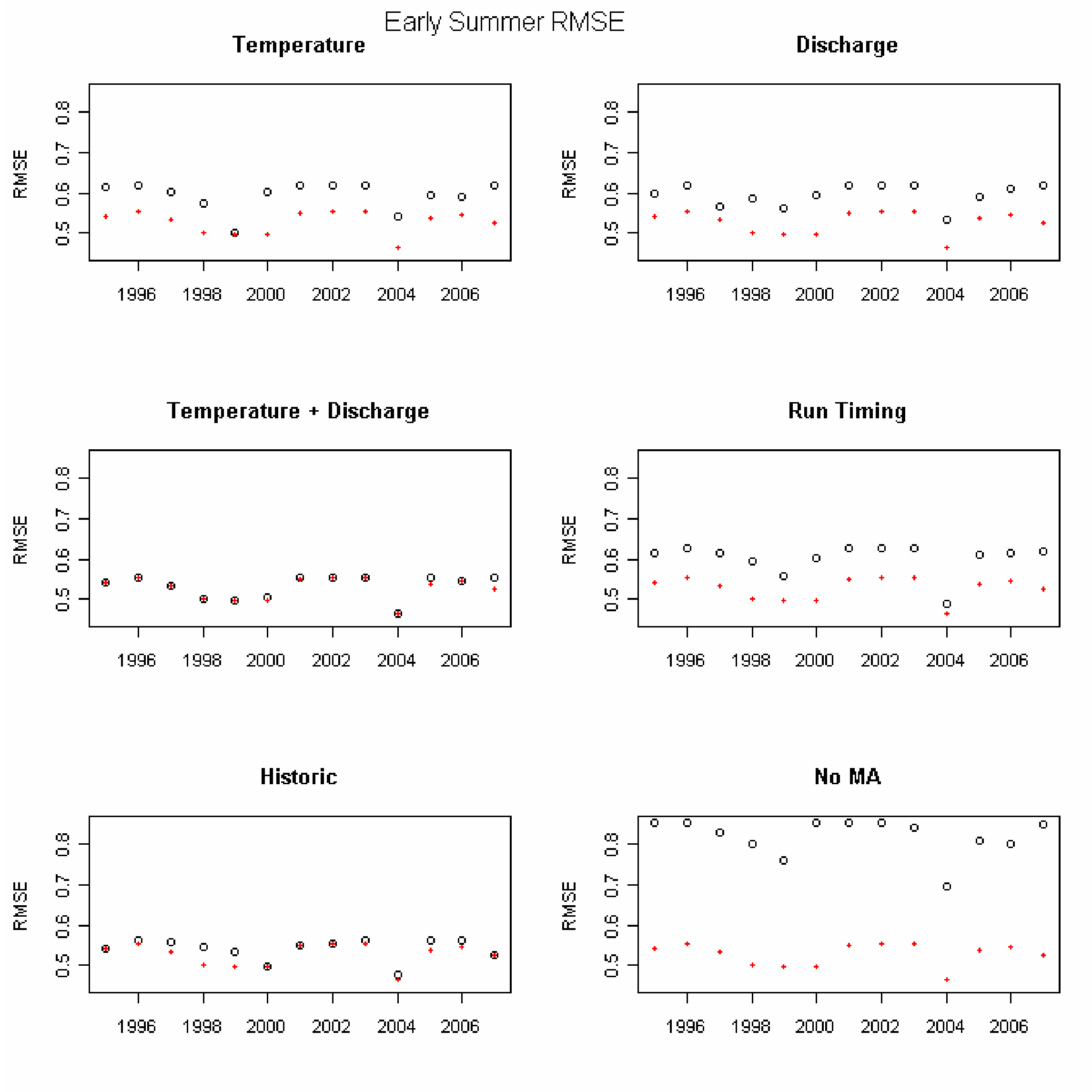

Early Stuart RMSE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
RMSE
0.6
0.8
1.0
1996
1998
2000
2002
2004
2006

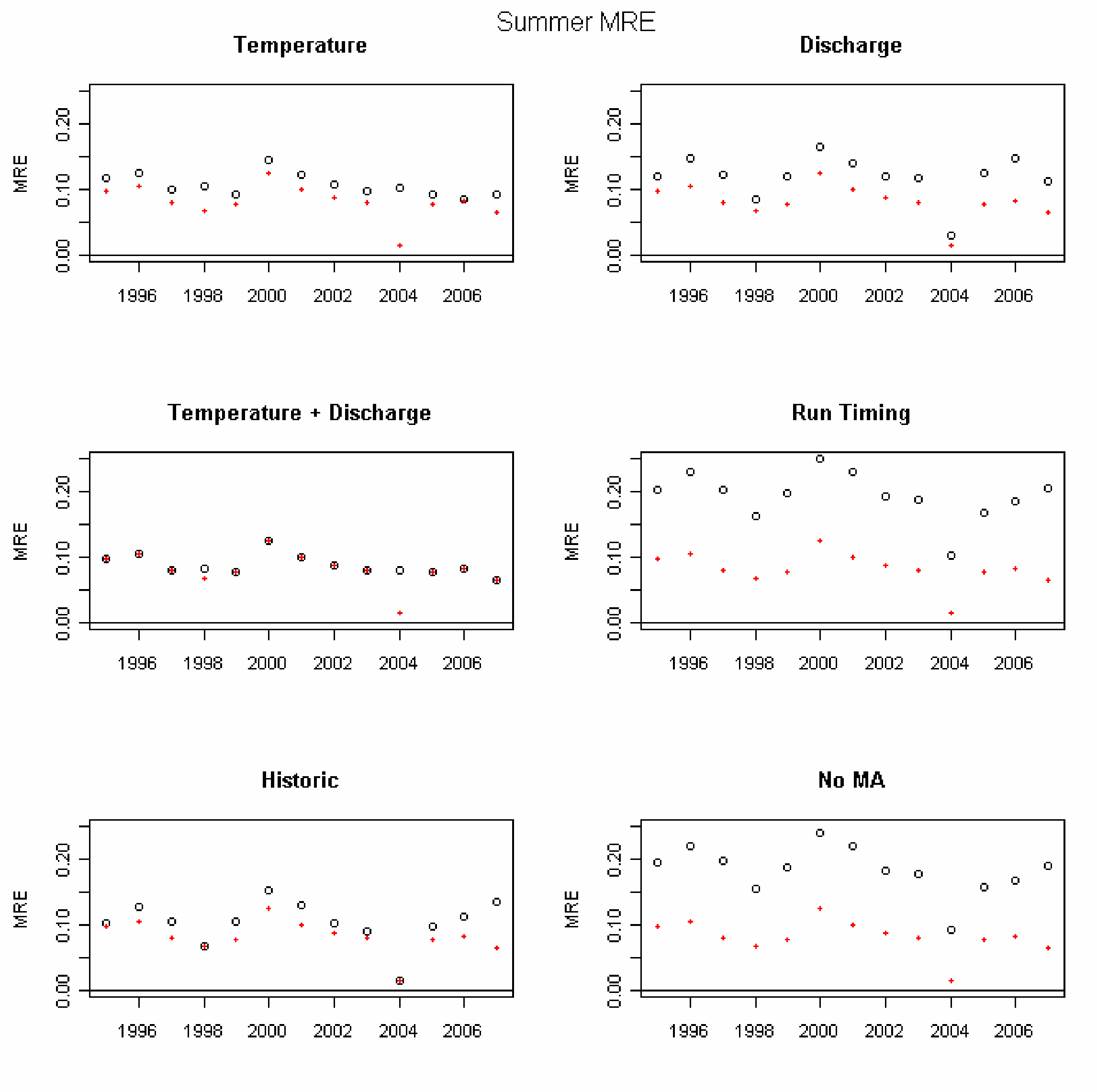


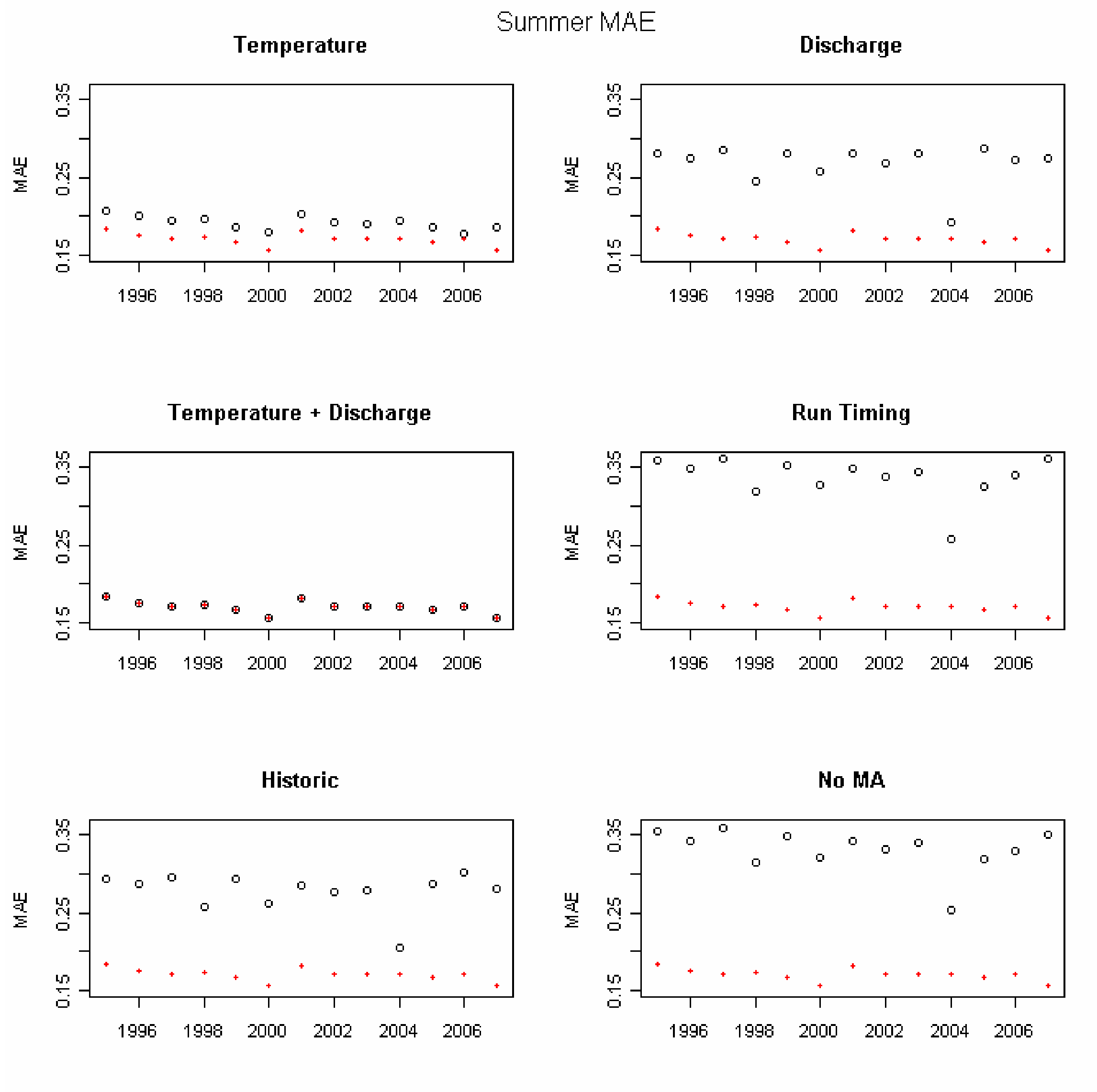
Early Summer MRE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MRE
0.0 0.2 0.4 0.6
1996 1998 2000 2002 2004 2006



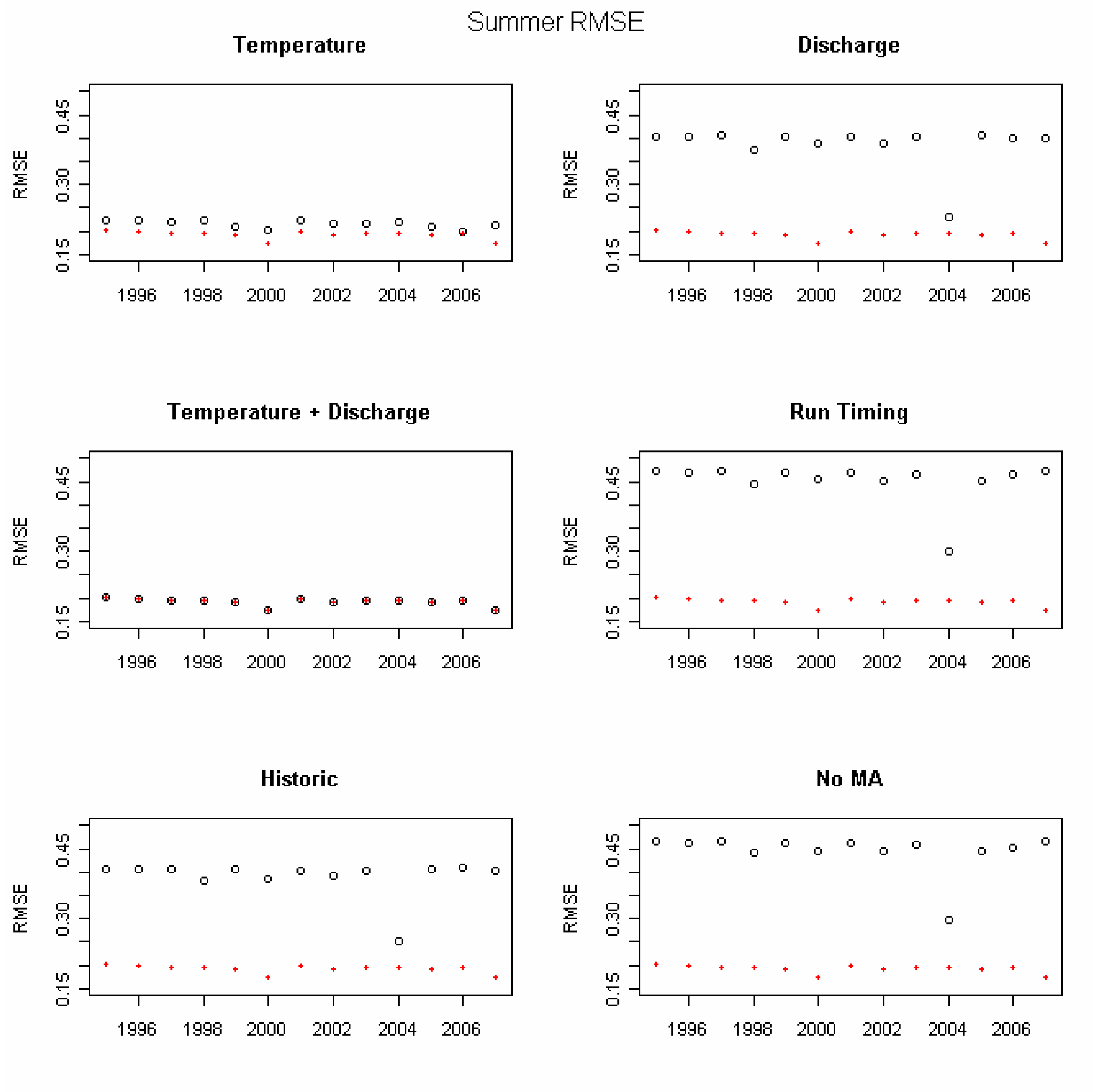
Early Summer MAE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MAE
0.35
0.50
0.65
1996
1998
2000
2002
2004
2006

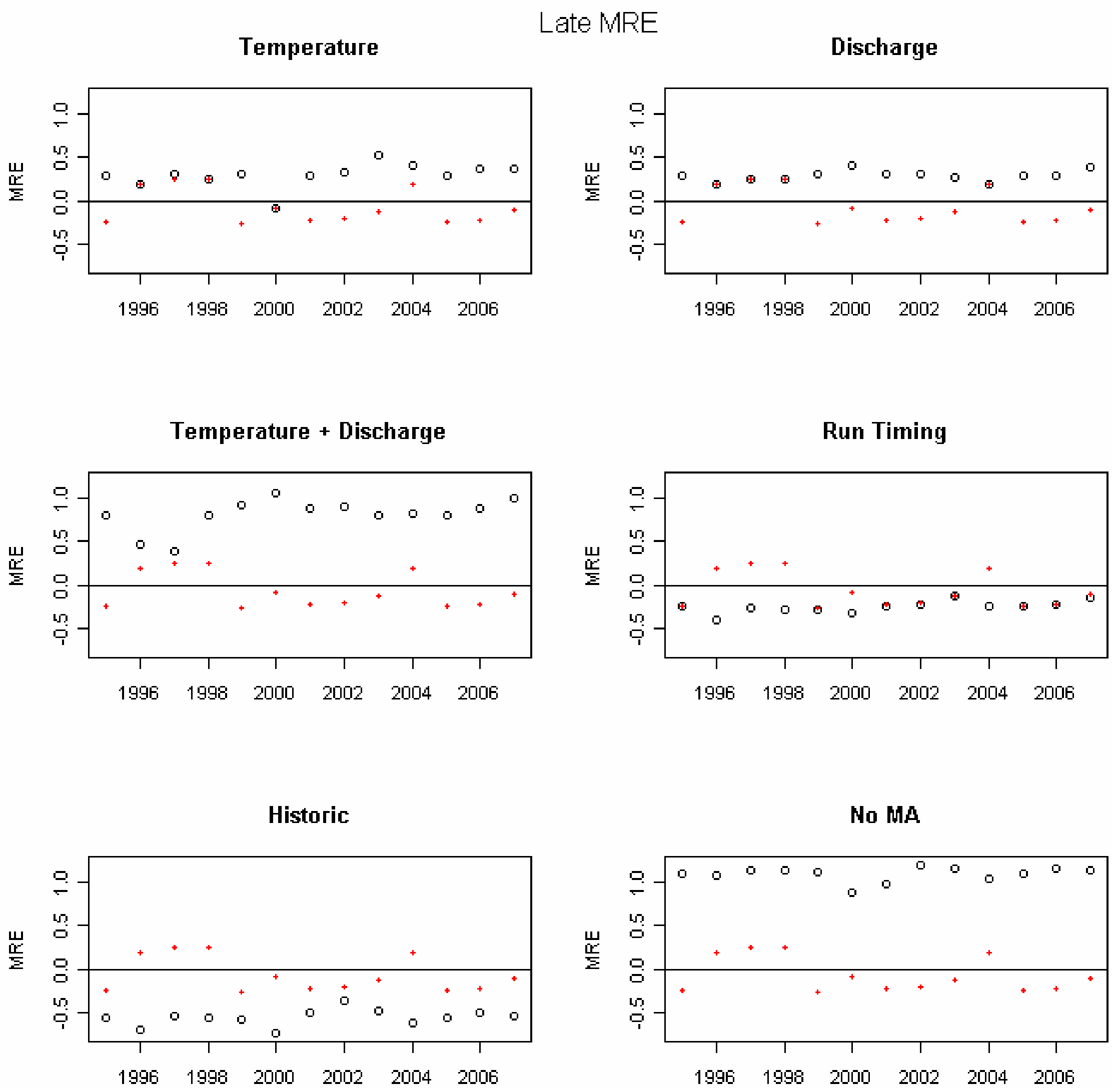

Early Summer RMSE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
RMSE
0.5
0.6
0.7
0.8
1996
1998
2000
2002
2004
2006

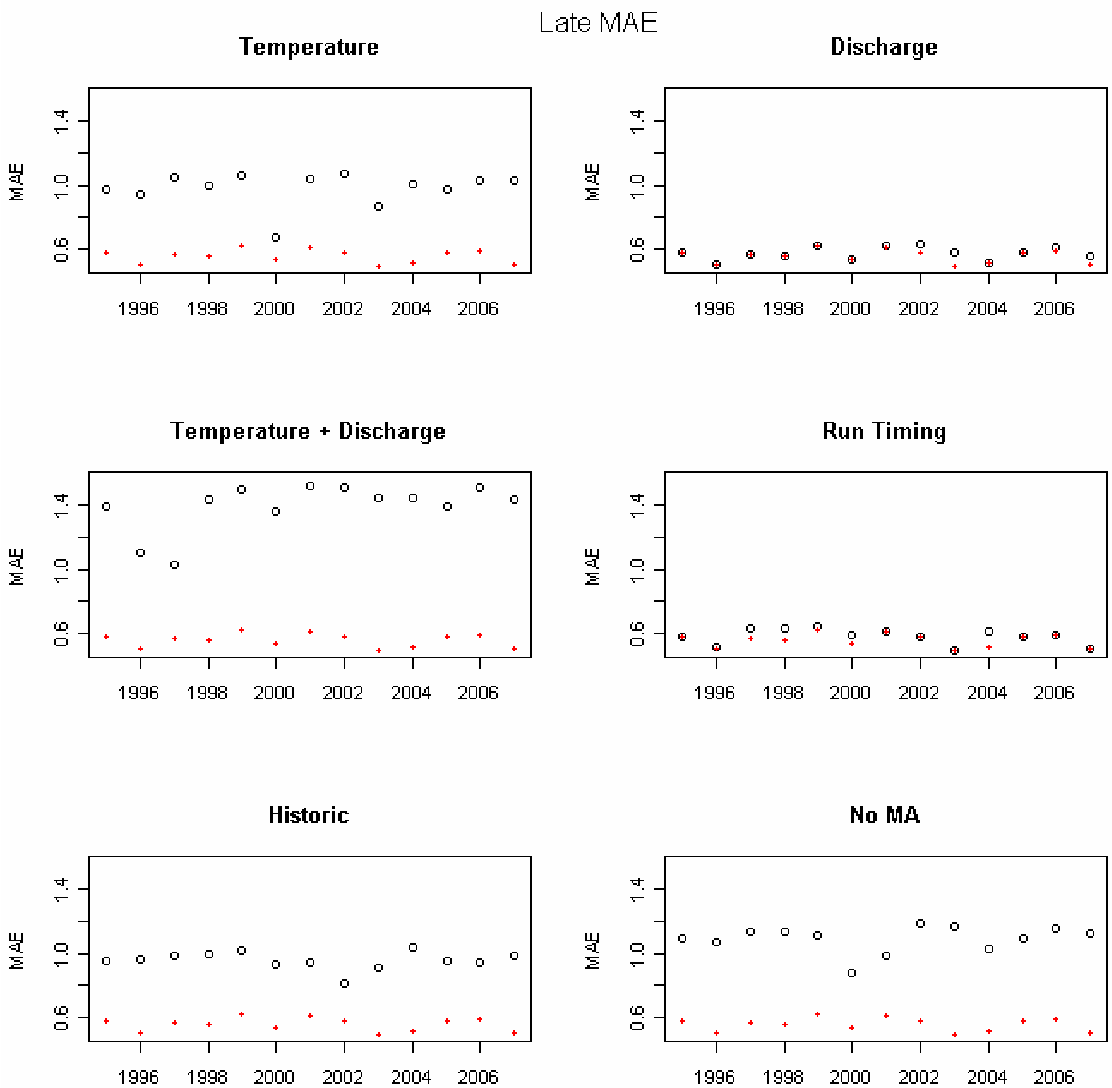

Summer MRE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MRE
0.00
0.10
0.20
1996
1998
2000
2002
2004
2006

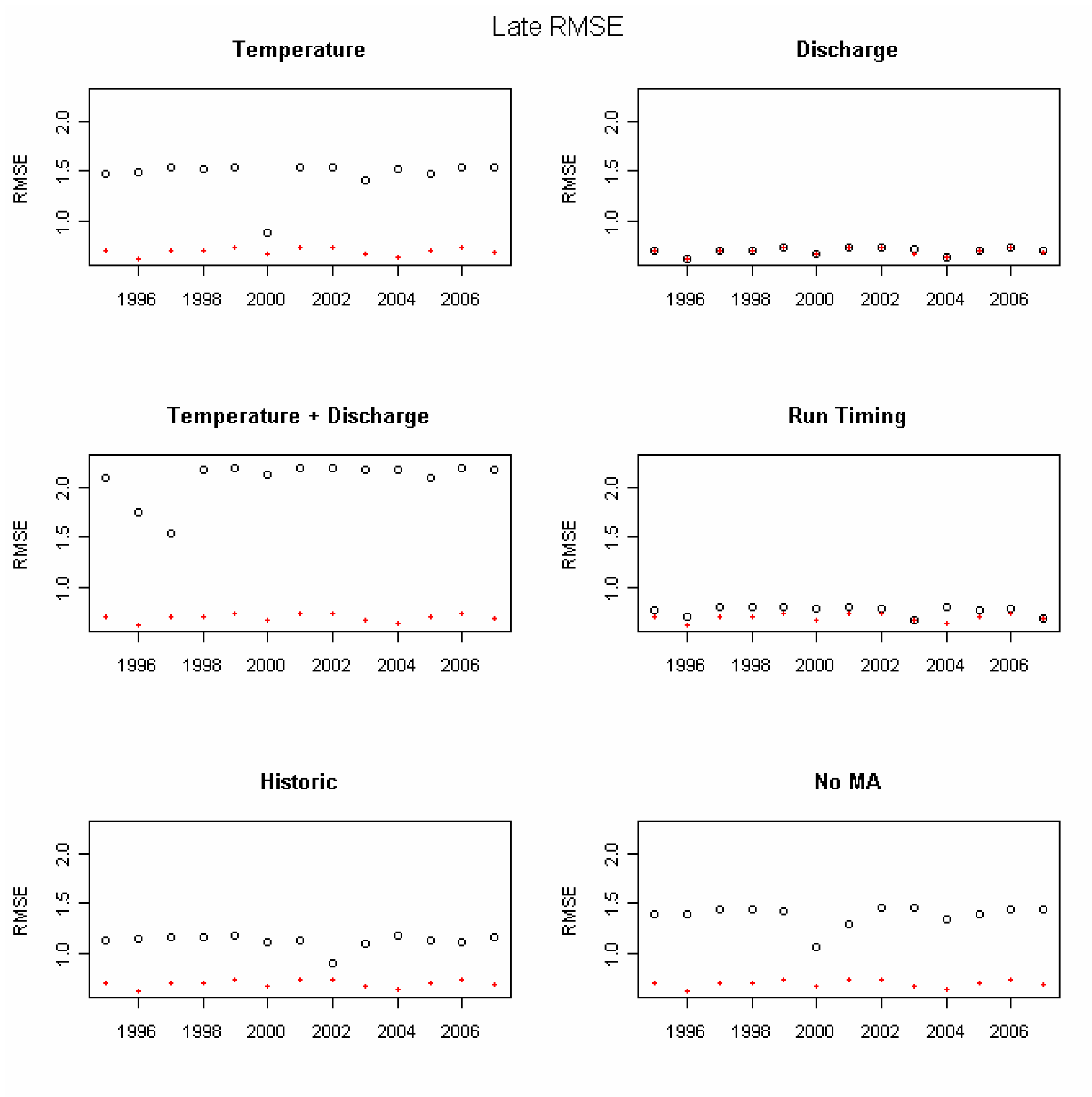


Summer MAE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MAE
0.15
0.25
0.35
1996
1998
2000
2002
2004
2006


Summer RMSE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
RMSE
0.15
0.30
0.45
1996
1998
2000
2002
2004
2006


Late MRE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MRE
-0.5 0.0 0.5 1.0
1996 1998 2000 2002 2004 2006


Late MAE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
MAE
0.6
1.0
1.4
1996
1998
2000
2002
2004
2006


Late RMSE
Temperature
Discharge
Temperature + Discharge
Run Timing
Historic
No MA
RMSE
1.0
1.5
2.0
1996
1998
2000
2002
2004
2006

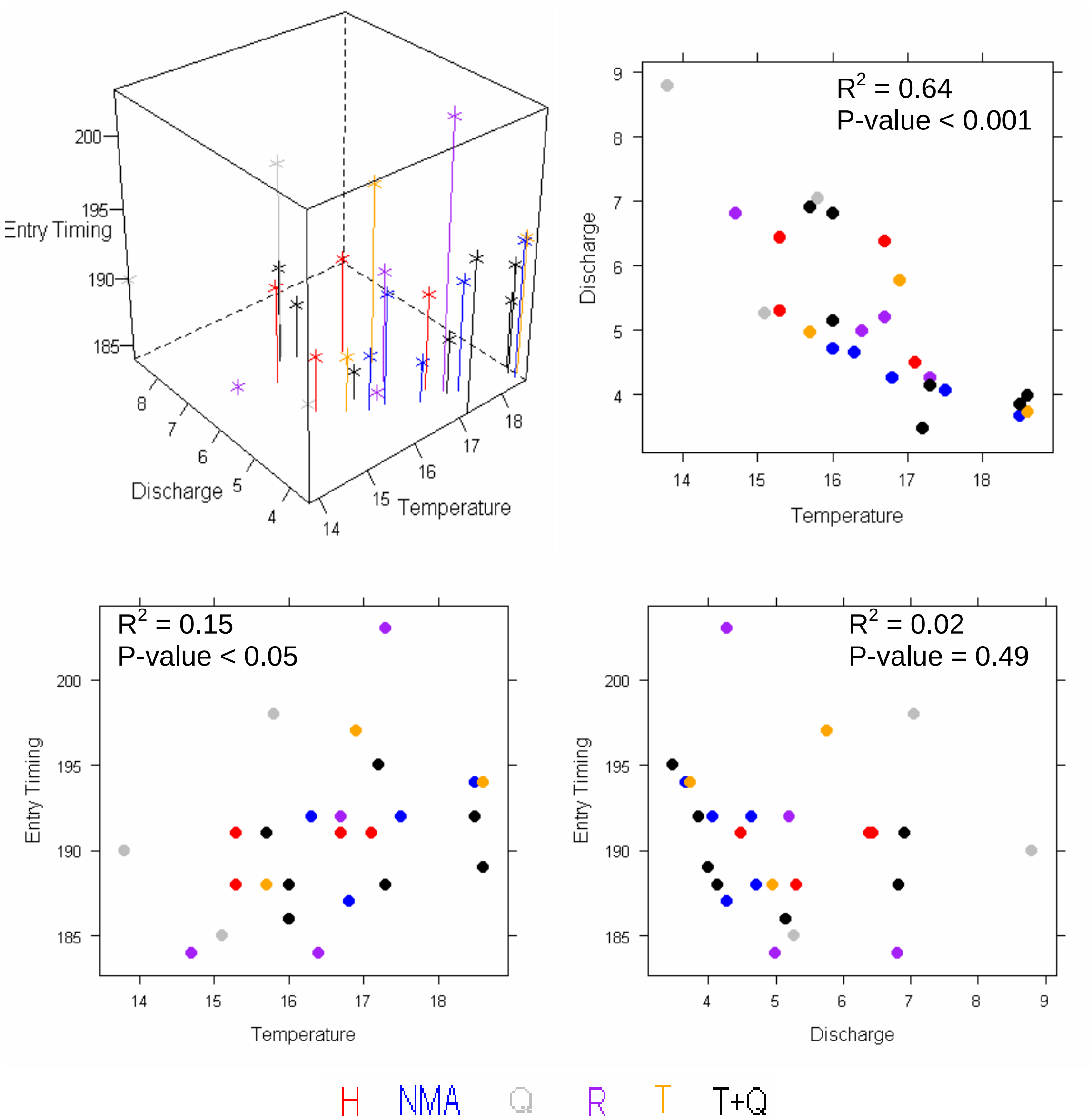
Appendix 3: Alternative Forecasting Techniques

Plots in this Appendix show the environmental conditions in each year in the past and the model that performed best in those environmental conditions (i.e., had the smallest raw error (RE, Eq. 7) in that year). To produce these plots, I used all of the management adjustment data available between 1977 and 2007 to conduct regressions. Using these full time series model fits, historical DBE forecasts were produced for each year of the historical time series. In each year, the model with the best forecast (i.e., the one with the smallest raw error) has been plotted. The positions of points on the graphs correspond to the environmental conditions present in the year of the model forecast, while the colors correspond to the model that performed best in the year that those environmental conditions occurred.

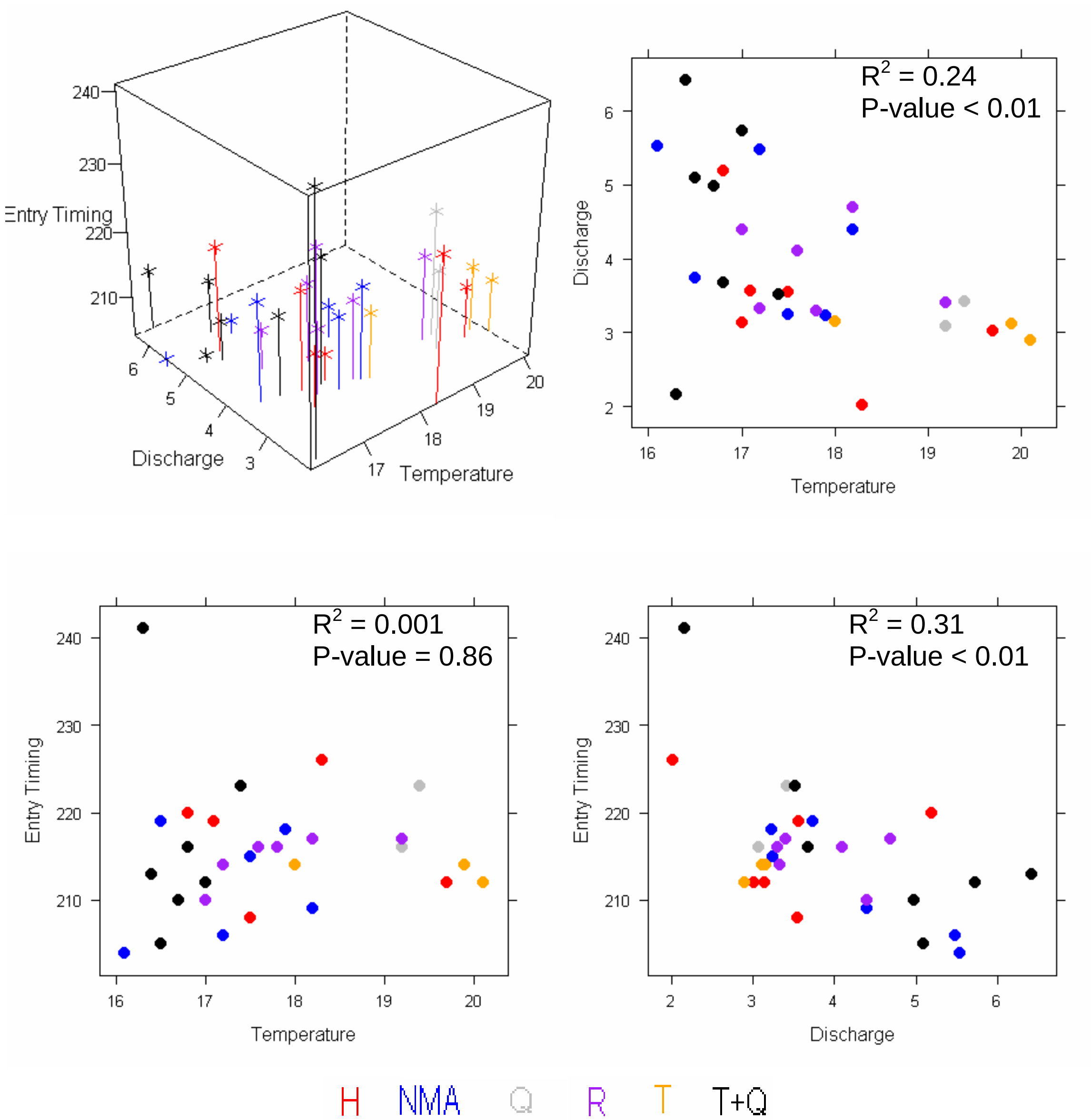
Multi-Dimensional Plots

The following plots show the best performing model based on either a set of two or three environmental conditions tracked every year during upstream migration of adult sockeye salmon (entry timing x discharge x temperature, discharge x temperature, entry timing x temperature, or entry timing x discharge). The variation in model selection is plotted as a function of entry timing (day), discharge (1,000s m^3/s), and or temperature (degrees C). Each colored point in the two- and three-dimensional plots below corresponds to the model that produced the smallest raw error in a given year historically. For the two dimensional plots, R^2 and p-values are shown for the association between the two variables.

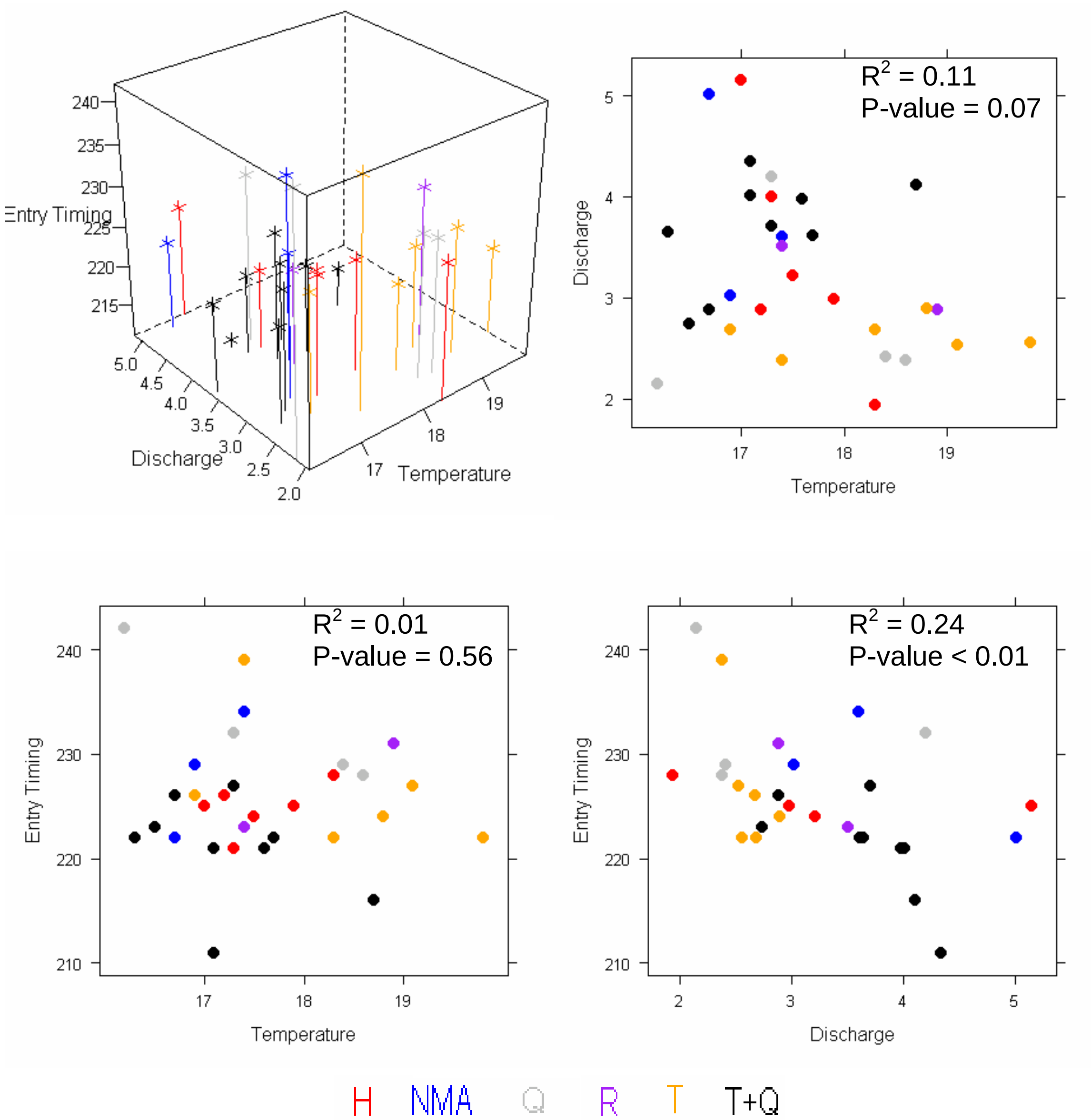
Early Stuart



Early Summer

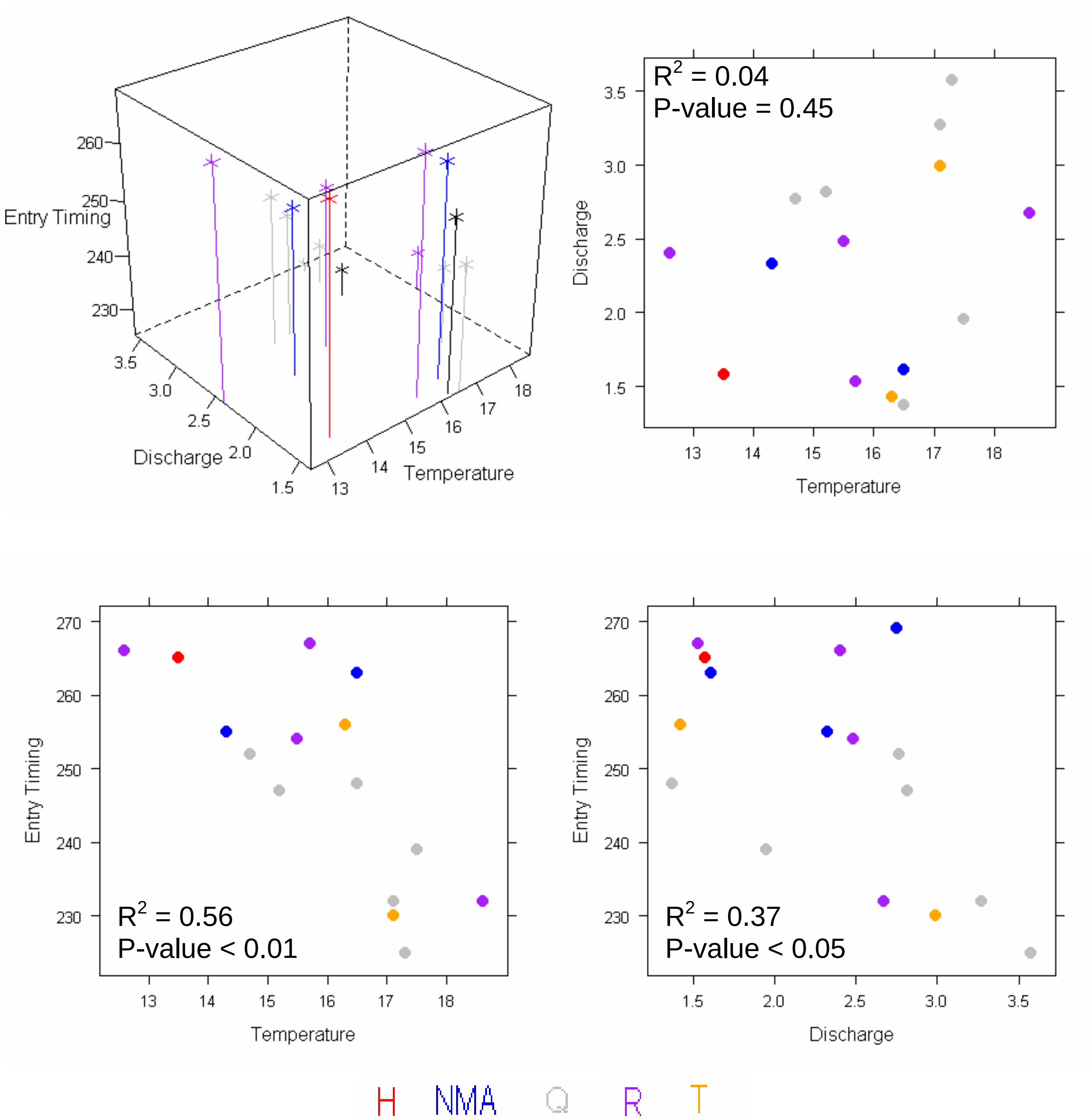


Summer



Entry Timing
240
235
230
225
220
215
5.0
4.5
4.0
3.5
3.0
2.5
2.0
Discharge
17
18
19
Temperature
$R^2 = 0.11$
P-value = 0.07
Discharge
5
4
3
2
17
18
19
Temperature
$R^2 = 0.01$
P-value = 0.56
Entry Timing
240
230
220
210
17
18
19
Temperature
$R^2 = 0.24$
P-value < 0.01
Entry Timing
240
230
220
210
2
3
4
5
Discharge
H
NMA
Q
R
T
T+Q

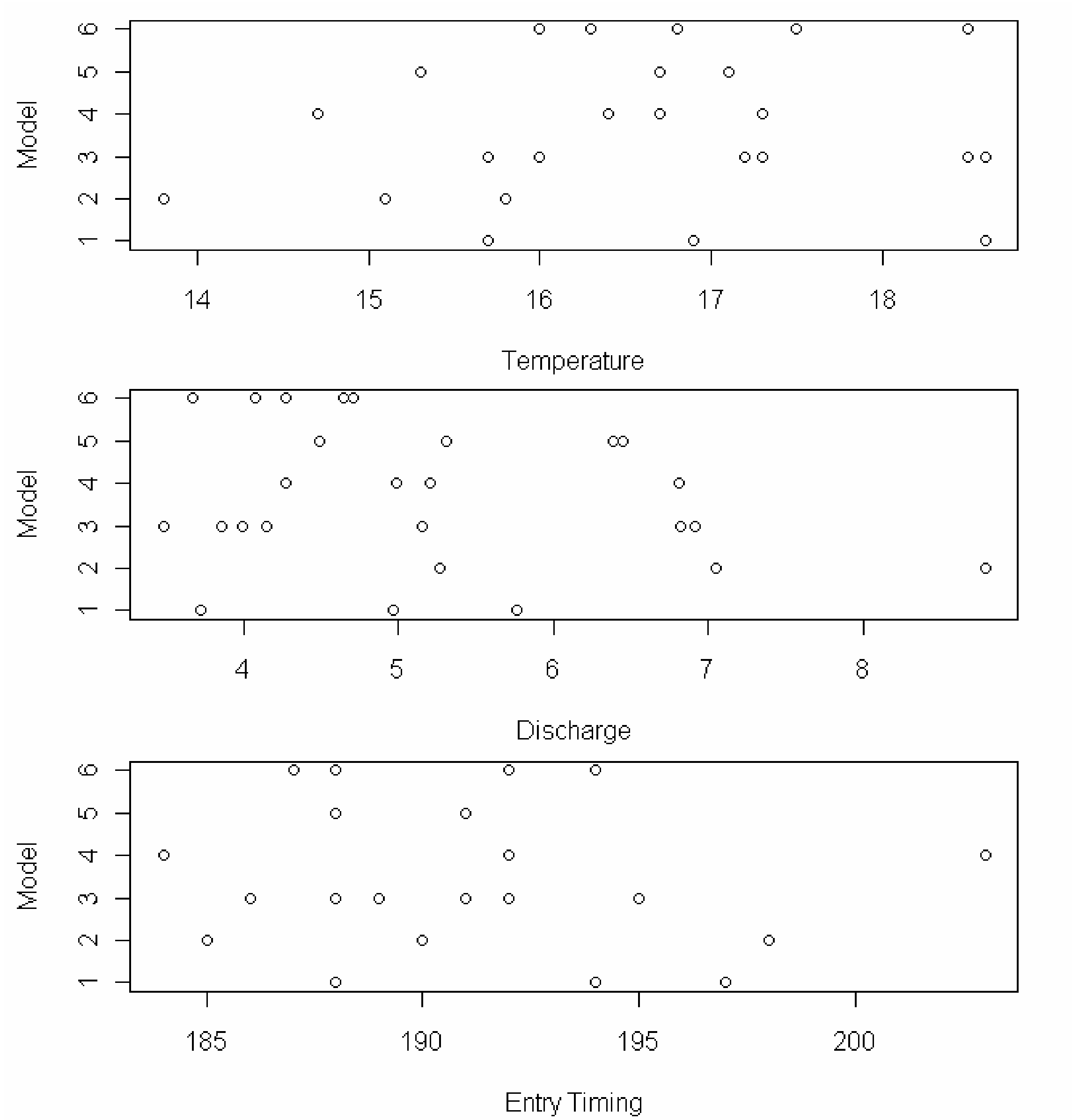
Late


Entry Timing
Discharge
Temperature
R2 = 0.04
P-value = 0.45
R2 = 0.56
P-value < 0.01
R2 = 0.37
P-value < 0.05
H
NMA
Q
R
T

Single-Dimension Plots

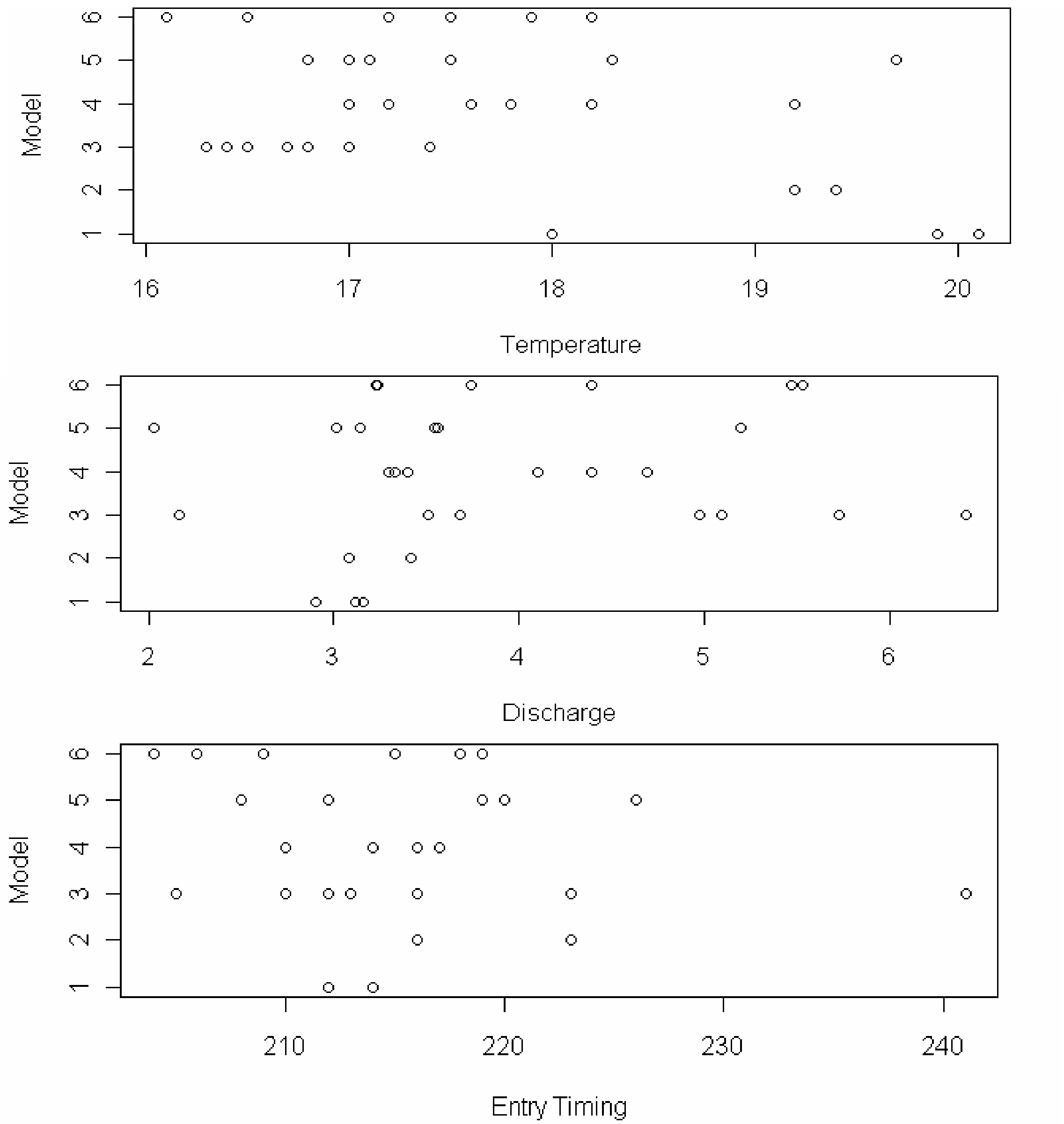
The following plots show the best performing model (the model with the smallest raw error) based on a single migration condition (entry timing, discharge, or temperature). Each point in the plots below corresponds to the model that produced the least raw error in a given year historically. The variation in model selection is plotted as a function of entry timing (day), discharge (1,000s m^3/s), and or temperature (degrees C).

Early Stuart



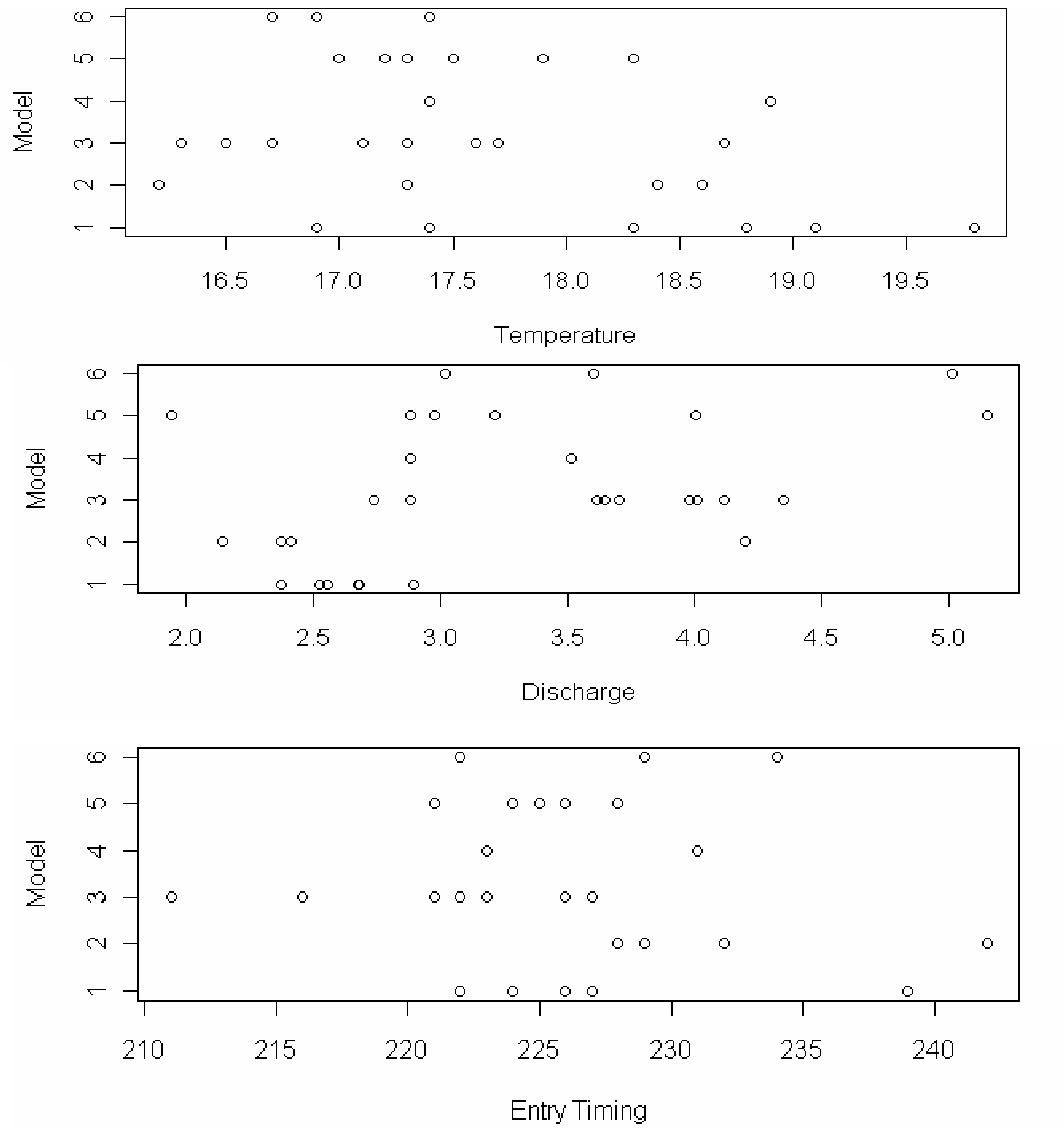
Model number (y axis #)	Model name
1.	Temperature
2.	Discharge
3.	Temperature-plus-discharge
4.	Run-timing
5.	Historic
6.	No MA

Early Summer



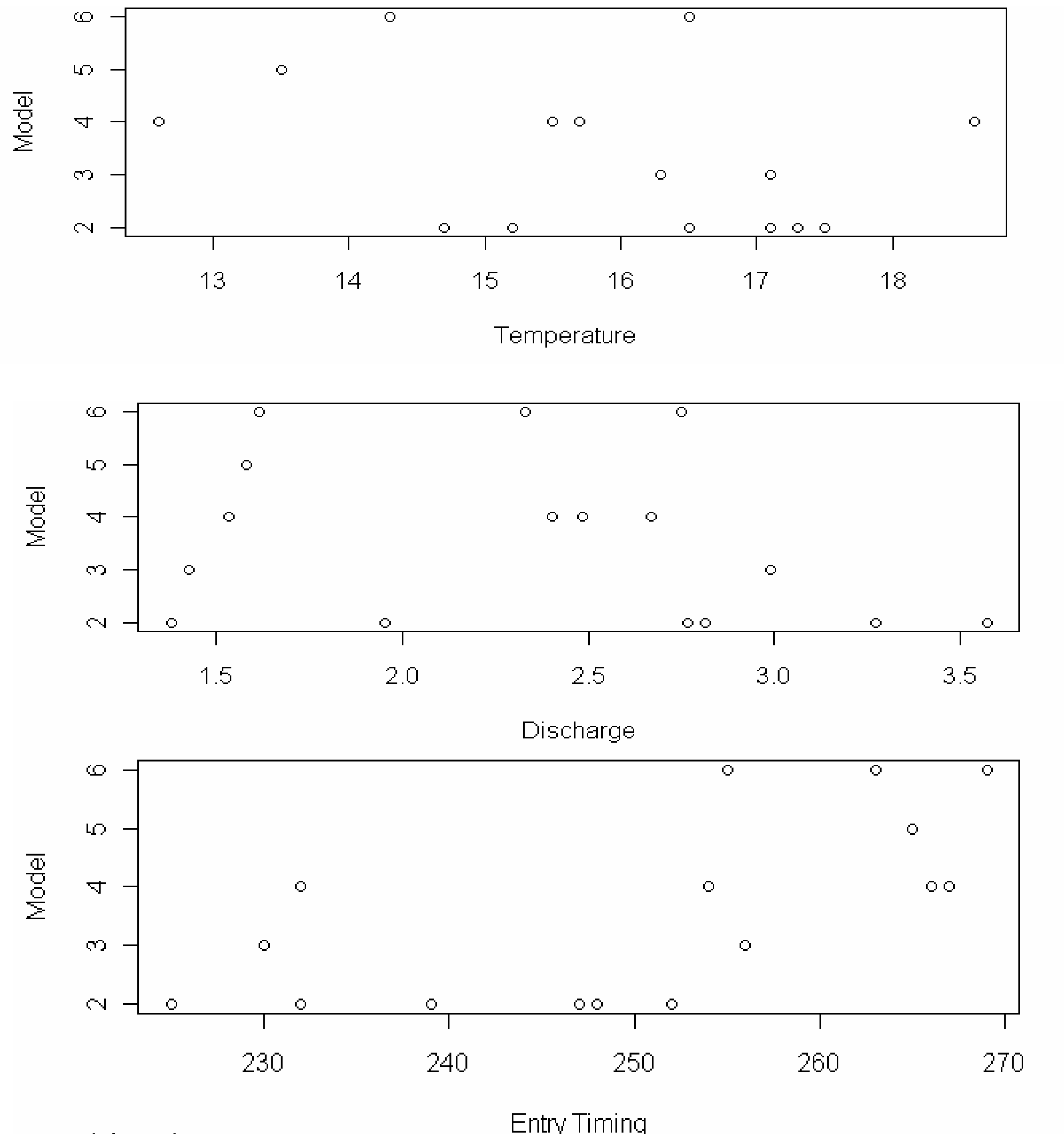
Model number (y axis #)	Model name
1.	Temperature
2.	Discharge
3.	Temperature-plus-discharge
4.	Run-timing
5.	Historic
6.	No MA

Summer



Model number (y axis #)	Model name
1.	Temperature
2.	Discharge
3.	Temperature-plus-discharge
4.	Run-timing
5.	Historic
6.	No MA

Late



Model number (y axis #)	Model name
1.	Temperature
2.	Discharge
3.	Temperature-plus-discharge
4.	Run-timing
5.	Historic
6.	No MA

Appendix 4: Asymmetric Loss Function Tables

Forecast Cost

These tables show the cost of each model's forecasting error for each of the four run-timing groups of Fraser River sockeye salmon for each asymmetric loss function examined. Highlighted cells indicate that for a given *O*:*U* ratio, the model with the highlighted cells performed best based on the weighted-average loss produced by the given *O*:*U* ratio. Each panel in a table corresponds to a model, which is indicated by capital letters in the top-left corner of each table and where T = temperature model , Q = discharge model, T+Q = temperature-plus-discharge model, R = run-timing model, H = historic model, and NMA = no management adjustment model. Historic model = , Temperature model = , Discharge model = , Temperature-plus-discharge model = , Run-timing model = . For example, in the top-left table, which is for the T model, there are only six *O*:*U* ratios (pink cells) for Early Stuart in which that T model is top ranked, whereas the Q model (top-right table) is best (blue cells) in cases of *O*:*U* ratios in the top-right corner.

Early Stuart

T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.12	0.13	0.13	0.14	0.15	0.16	0.18	0.19	0.21	0.22
0.6	0.12	0.13	0.14	0.15	0.15	0.16	0.18	0.19	0.21	0.22	0.24
0.7	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.21	0.22	0.24	0.25
0.8	0.15	0.16	0.17	0.18	0.18	0.19	0.21	0.22	0.24	0.25	0.27
0.9	0.17	0.18	0.18	0.19	0.20	0.21	0.22	0.24	0.25	0.27	0.28
1	0.18	0.19	0.20	0.20	0.21	0.22	0.24	0.25	0.27	0.28	0.30
1.2	0.21	0.22	0.23	0.23	0.24	0.25	0.26	0.28	0.29	0.31	0.33
1.4	0.24	0.25	0.25	0.26	0.27	0.28	0.29	0.31	0.32	0.34	0.35
1.6	0.27	0.28	0.28	0.29	0.30	0.31	0.32	0.34	0.35	0.37	0.38
1.8	0.30	0.30	0.31	0.32	0.33	0.34	0.35	0.37	0.38	0.40	0.41
2	0.33	0.33	0.34	0.35	0.36	0.36	0.38	0.39	0.41	0.42	0.44

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.12	0.12	0.13	0.13	0.14	0.15	0.16	0.17	0.18	0.19
0.6	0.13	0.14	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.20	0.21
0.7	0.15	0.16	0.16	0.17	0.17	0.18	0.18	0.19	0.20	0.21	0.22
0.8	0.17	0.17	0.18	0.18	0.19	0.19	0.20	0.21	0.22	0.23	0.24
0.9	0.19	0.19	0.20	0.20	0.21	0.21	0.22	0.23	0.24	0.25	0.26
1	0.20	0.21	0.21	0.22	0.22	0.23	0.24	0.25	0.26	0.27	0.28
1.2	0.24	0.25	0.25	0.26	0.26	0.27	0.27	0.28	0.29	0.30	0.31
1.4	0.28	0.28	0.29	0.29	0.30	0.30	0.31	0.32	0.33	0.34	0.35
1.6	0.31	0.32	0.32	0.33	0.33	0.34	0.35	0.36	0.37	0.38	0.39
1.8	0.35	0.35	0.36	0.36	0.37	0.37	0.38	0.39	0.40	0.41	0.42
2	0.38	0.39	0.39	0.40	0.40	0.41	0.42	0.43	0.44	0.45	0.46

T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.13	0.13	0.14	0.15	0.15	0.16	0.17	0.19	0.20	0.22	0.23
0.6	0.14	0.15	0.16	0.16	0.17	0.18	0.19	0.21	0.22	0.23	0.25
0.7	0.16	0.17	0.18	0.18	0.19	0.20	0.21	0.22	0.24	0.25	0.27
0.8	0.18	0.19	0.19	0.20	0.21	0.22	0.23	0.24	0.26	0.27	0.28
0.9	0.20	0.21	0.21	0.22	0.23	0.23	0.25	0.26	0.28	0.29	0.30
1	0.22	0.22	0.23	0.24	0.24	0.25	0.27	0.28	0.29	0.31	0.32
1.2	0.25	0.26	0.27	0.27	0.28	0.29	0.30	0.32	0.33	0.34	0.36
1.4	0.29	0.30	0.30	0.31	0.32	0.32	0.34	0.35	0.37	0.38	0.39
1.6	0.33	0.33	0.34	0.35	0.35	0.36	0.38	0.39	0.40	0.42	0.43
1.8	0.36	0.37	0.38	0.38	0.39	0.40	0.41	0.43	0.44	0.45	0.47
2	0.40	0.41	0.41	0.42	0.43	0.43	0.45	0.46	0.48	0.49	0.50

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.12	0.13	0.13	0.14	0.14	0.15	0.16	0.17	0.18	0.19
0.6	0.13	0.14	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.20	0.21
0.7	0.15	0.16	0.16	0.17	0.17	0.18	0.19	0.20	0.21	0.22	0.23
0.8	0.17	0.17	0.18	0.18	0.19	0.19	0.20	0.22	0.23	0.24	0.25
0.9	0.19	0.19	0.20	0.20	0.21	0.21	0.22	0.23	0.24	0.25	0.26
1	0.20	0.21	0.21	0.22	0.22	0.23	0.24	0.25	0.26	0.27	0.28
1.2	0.24	0.24	0.25	0.25	0.26	0.27	0.28	0.29	0.30	0.31	0.32
1.4	0.27	0.28	0.29	0.29	0.30	0.30	0.31	0.32	0.33	0.34	0.35
1.6	0.31	0.32	0.32	0.33	0.33	0.34	0.35	0.36	0.37	0.38	0.39
1.8	0.35	0.35	0.36	0.36	0.37	0.37	0.38	0.39	0.40	0.41	0.42
2	0.38	0.39	0.39	0.40	0.40	0.41	0.42	0.43	0.44	0.45	0.46

H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.12	0.13	0.14	0.15	0.17	0.19	0.21	0.24	0.26	0.28
0.6	0.12	0.13	0.14	0.15	0.16	0.18	0.20	0.22	0.25	0.27	0.29
0.7	0.12	0.14	0.15	0.16	0.17	0.18	0.21	0.23	0.26	0.28	0.30
0.8	0.13	0.15	0.16	0.17	0.18	0.19	0.22	0.24	0.27	0.29	0.31
0.9	0.14	0.16	0.17	0.18	0.19	0.20	0.23	0.25	0.27	0.30	0.32
1	0.15	0.16	0.18	0.19	0.20	0.21	0.24	0.26	0.28	0.31	0.33
1.2	0.17	0.18	0.20	0.21	0.22	0.23	0.25	0.28	0.30	0.33	0.35
1.4	0.19	0.20	0.21	0.23	0.24	0.25	0.27	0.30	0.32	0.34	0.37
1.6	0.21	0.22	0.23	0.24	0.26	0.27	0.29	0.32	0.34	0.36	0.39
1.8	0.23	0.24	0.25	0.26	0.27	0.29	0.31	0.33	0.36	0.38	0.41
2	0.25	0.26	0.27	0.28	0.29	0.31	0.33	0.35	0.38	0.40	0.42

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26
0.6	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
0.7	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
0.8	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
0.9	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
1	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52
1.2	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
1.4	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
1.6	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
1.8	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
2	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05

Early Summer

O

	T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.13	0.13	0.14	0.15	0.15	0.16	0.17	0.19	0.20	0.21	0.23
	0.6	0.14	0.15	0.16	0.16	0.17	0.18	0.19	0.20	0.22	0.23	0.24
	0.7	0.16	0.17	0.18	0.18	0.19	0.20	0.21	0.22	0.24	0.25	0.26
	0.8	0.18	0.19	0.19	0.20	0.21	0.21	0.23	0.24	0.25	0.27	0.28
U	0.9	0.20	0.21	0.21	0.22	0.23	0.23	0.25	0.26	0.27	0.29	0.30
	1	0.22	0.22	0.23	0.24	0.24	0.25	0.26	0.28	0.29	0.30	0.32
	1.2	0.25	0.26	0.27	0.27	0.28	0.29	0.30	0.31	0.33	0.34	0.35
	1.4	0.29	0.30	0.30	0.31	0.32	0.32	0.34	0.35	0.36	0.38	0.39
	1.6	0.33	0.34	0.34	0.35	0.35	0.36	0.37	0.39	0.40	0.41	0.43
	1.8	0.37	0.37	0.38	0.39	0.39	0.40	0.41	0.43	0.44	0.45	0.47
	2	0.40	0.41	0.42	0.42	0.43	0.44	0.45	0.46	0.48	0.49	0.50

O

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.13	0.14	0.15	0.16	0.17	0.19	0.21	0.23	0.26	0.28	0.30
0.6	0.14	0.15	0.16	0.18	0.19	0.20	0.22	0.25	0.27	0.29	0.32
0.7	0.15	0.17	0.18	0.19	0.20	0.21	0.24	0.26	0.28	0.31	0.33
0.8	0.17	0.18	0.19	0.20	0.22	0.23	0.25	0.27	0.30	0.32	0.34
0.9	0.18	0.19	0.21	0.22	0.23	0.24	0.26	0.29	0.31	0.33	0.36
1	0.20	0.21	0.22	0.23	0.24	0.25	0.28	0.30	0.32	0.35	0.37
1.2	0.22	0.24	0.25	0.26	0.27	0.28	0.31	0.33	0.35	0.37	0.40
1.4	0.25	0.26	0.27	0.29	0.30	0.31	0.33	0.36	0.38	0.40	0.43
1.6	0.28	0.29	0.30	0.31	0.33	0.34	0.36	0.38	0.41	0.43	0.45
1.8	0.31	0.32	0.33	0.34	0.35	0.36	0.39	0.41	0.43	0.46	0.48
2	0.33	0.35	0.36	0.37	0.38	0.39	0.42	0.44	0.46	0.49	0.51

	T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.11	0.12	0.13	0.14	0.15	0.16	0.18	0.19	0.21	0.23	0.25
	0.6	0.13	0.13	0.14	0.15	0.16	0.17	0.19	0.21	0.23	0.24	0.26
	0.7	0.14	0.15	0.16	0.17	0.18	0.18	0.20	0.22	0.24	0.26	0.28
	0.8	0.15	0.16	0.17	0.18	0.19	0.20	0.22	0.23	0.25	0.27	0.29
	0.9	0.17	0.17	0.18	0.19	0.20	0.21	0.23	0.25	0.27	0.28	0.30
U	1	0.18	0.19	0.20	0.21	0.22	0.22	0.24	0.26	0.28	0.30	0.32
	1.2	0.21	0.21	0.22	0.23	0.24	0.25	0.27	0.29	0.31	0.32	0.34
	1.4	0.23	0.24	0.25	0.26	0.27	0.28	0.30	0.31	0.33	0.35	0.37
	1.6	0.26	0.27	0.28	0.29	0.29	0.30	0.32	0.34	0.36	0.38	0.40
	1.8	0.29	0.29	0.30	0.31	0.32	0.33	0.35	0.37	0.39	0.40	0.42
	2	0.31	0.32	0.33	0.34	0.35	0.36	0.38	0.39	0.41	0.43	0.45

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.14	0.15	0.16	0.17	0.19	0.20	0.22	0.24	0.27	0.29	0.31
0.6	0.16	0.17	0.18	0.19	0.20	0.21	0.24	0.26	0.28	0.31	0.33
0.7	0.17	0.18	0.20	0.21	0.22	0.23	0.25	0.28	0.30	0.32	0.35
0.8	0.19	0.20	0.21	0.22	0.24	0.25	0.27	0.29	0.32	0.34	0.36
0.9	0.21	0.22	0.23	0.24	0.25	0.26	0.29	0.31	0.33	0.36	0.38
1	0.22	0.23	0.24	0.26	0.27	0.28	0.30	0.33	0.35	0.37	0.40
1.2	0.25	0.27	0.28	0.29	0.30	0.31	0.34	0.36	0.38	0.40	0.43
1.4	0.29	0.30	0.31	0.32	0.33	0.34	0.37	0.39	0.41	0.44	0.46
1.6	0.32	0.33	0.34	0.35	0.37	0.38	0.40	0.42	0.45	0.47	0.49
1.8	0.35	0.36	0.38	0.39	0.40	0.41	0.43	0.46	0.48	0.50	0.53
2	0.39	0.40	0.41	0.42	0.43	0.44	0.47	0.49	0.51	0.54	0.56

	H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.13	0.14	0.16	0.18	0.20	0.21	0.25	0.28	0.32	0.35	0.39
	0.6	0.13	0.15	0.17	0.19	0.20	0.22	0.26	0.29	0.33	0.36	0.40
	0.7	0.14	0.16	0.18	0.19	0.21	0.23	0.26	0.30	0.33	0.37	0.40
	0.8	0.15	0.17	0.18	0.20	0.22	0.24	0.27	0.31	0.34	0.38	0.41
	0.9	0.16	0.17	0.19	0.21	0.23	0.24	0.28	0.31	0.35	0.38	0.42
U	1	0.16	0.18	0.20	0.22	0.23	0.25	0.29	0.32	0.36	0.39	0.43
	1.2	0.18	0.20	0.21	0.23	0.25	0.27	0.30	0.34	0.37	0.41	0.44
	1.4	0.19	0.21	0.23	0.25	0.26	0.28	0.32	0.35	0.39	0.42	0.46
	1.6	0.21	0.23	0.24	0.26	0.28	0.30	0.33	0.37	0.40	0.44	0.47
	1.8	0.22	0.24	0.26	0.28	0.29	0.31	0.35	0.38	0.42	0.45	0.49
	2	0.24	0.26	0.27	0.29	0.31	0.33	0.36	0.40	0.43	0.47	0.50

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.21	0.21	0.21	0.21	0.22	0.22	0.22	0.23	0.23	0.23	0.24
0.6	0.25	0.25	0.25	0.25	0.25	0.26	0.26	0.27	0.27	0.27	0.28
0.7	0.29	0.29	0.29	0.29	0.29	0.30	0.30	0.30	0.31	0.31	0.32
0.8	0.32	0.33	0.33	0.33	0.33	0.33	0.34	0.34	0.35	0.35	0.36
0.9	0.36	0.37	0.37	0.37	0.37	0.37	0.38	0.38	0.39	0.39	0.40
1	0.40	0.40	0.41	0.41	0.41	0.41	0.42	0.42	0.43	0.43	0.43
1.2	0.48	0.48	0.49	0.49	0.49	0.49	0.50	0.50	0.50	0.51	0.51
1.4	0.56	0.56	0.56	0.57	0.57	0.57	0.57	0.58	0.58	0.59	0.59
1.6	0.64	0.64	0.64	0.64	0.65	0.65	0.65	0.66	0.66	0.67	0.67
1.8	0.72	0.72	0.72	0.72	0.72	0.73	0.73	0.74	0.74	0.74	0.75
2	0.79	0.80	0.80	0.80	0.80	0.81	0.81	0.81	0.82	0.82	0.83

Summer

O

	T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.09	0.09	0.10	0.11	0.11	0.12	0.13	0.14	0.15	0.16	0.17
	0.6	0.10	0.11	0.11	0.12	0.12	0.13	0.14	0.15	0.16	0.17	0.18
	0.7	0.11	0.12	0.13	0.13	0.14	0.14	0.15	0.16	0.17	0.18	0.20
	0.8	0.13	0.13	0.14	0.14	0.15	0.15	0.16	0.18	0.19	0.20	0.21
	0.9	0.14	0.14	0.15	0.16	0.16	0.17	0.18	0.19	0.20	0.21	0.22
U	1	0.15	0.16	0.16	0.17	0.17	0.18	0.19	0.20	0.21	0.22	0.23
	1.2	0.18	0.18	0.19	0.19	0.20	0.20	0.21	0.23	0.24	0.25	0.26
	1.4	0.20	0.21	0.21	0.22	0.22	0.23	0.24	0.25	0.26	0.27	0.28
	1.6	0.23	0.23	0.24	0.24	0.25	0.25	0.26	0.28	0.29	0.30	0.31
	1.8	0.25	0.26	0.26	0.27	0.27	0.28	0.29	0.30	0.31	0.32	0.33
	2	0.28	0.28	0.29	0.29	0.30	0.30	0.31	0.33	0.34	0.35	0.36

O

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.12	0.13	0.13	0.14	0.15	0.17	0.18	0.20	0.22	0.23
0.6	0.12	0.13	0.14	0.15	0.16	0.16	0.18	0.20	0.21	0.23	0.25
0.7	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.21	0.23	0.24	0.26
0.8	0.15	0.16	0.17	0.18	0.18	0.19	0.21	0.22	0.24	0.26	0.27
0.9	0.17	0.17	0.18	0.19	0.20	0.21	0.22	0.24	0.25	0.27	0.29
1	0.18	0.19	0.20	0.20	0.21	0.22	0.24	0.25	0.27	0.28	0.30
1.2	0.21	0.22	0.22	0.23	0.24	0.25	0.26	0.28	0.30	0.31	0.33
1.4	0.24	0.24	0.25	0.26	0.27	0.28	0.29	0.31	0.32	0.34	0.36
1.6	0.26	0.27	0.28	0.29	0.30	0.30	0.32	0.34	0.35	0.37	0.38
1.8	0.29	0.30	0.31	0.32	0.32	0.33	0.35	0.36	0.38	0.40	0.41
2	0.32	0.33	0.34	0.34	0.35	0.36	0.38	0.39	0.41	0.42	0.44

	T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.08	0.09	0.09	0.10	0.10	0.11	0.12	0.13	0.14	0.15	0.16
	0.6	0.09	0.10	0.10	0.11	0.11	0.12	0.13	0.14	0.15	0.16	0.17
	0.7	0.10	0.11	0.11	0.12	0.12	0.13	0.14	0.15	0.16	0.17	0.18
	0.8	0.11	0.12	0.12	0.13	0.13	0.14	0.15	0.16	0.17	0.18	0.19
	0.9	0.12	0.13	0.13	0.14	0.14	0.15	0.16	0.17	0.18	0.19	0.20
U	1	0.13	0.14	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.20	0.21
	1.2	0.15	0.16	0.17	0.17	0.18	0.18	0.19	0.20	0.21	0.22	0.23
	1.4	0.18	0.18	0.19	0.19	0.20	0.20	0.21	0.22	0.23	0.24	0.25
	1.6	0.20	0.20	0.21	0.21	0.22	0.22	0.23	0.24	0.26	0.27	0.28
	1.8	0.22	0.22	0.23	0.24	0.24	0.25	0.26	0.27	0.28	0.29	0.30
	2	0.24	0.25	0.25	0.26	0.26	0.27	0.28	0.29	0.30	0.31	0.32

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.14	0.15	0.16	0.17	0.18	0.19	0.20	0.22	0.24	0.25	0.27
0.6	0.16	0.17	0.18	0.19	0.20	0.21	0.22	0.24	0.26	0.27	0.29
0.7	0.18	0.19	0.20	0.21	0.22	0.23	0.24	0.26	0.28	0.29	0.31
0.8	0.20	0.21	0.22	0.23	0.24	0.25	0.26	0.28	0.30	0.31	0.33
0.9	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.30	0.32	0.33	0.35
1	0.24	0.25	0.26	0.27	0.28	0.29	0.30	0.32	0.34	0.35	0.37
1.2	0.28	0.29	0.30	0.31	0.32	0.33	0.34	0.36	0.38	0.39	0.41
1.4	0.32	0.33	0.34	0.35	0.36	0.37	0.38	0.40	0.42	0.43	0.45
1.6	0.36	0.37	0.38	0.39	0.40	0.41	0.42	0.44	0.46	0.47	0.49
1.8	0.40	0.41	0.42	0.43	0.44	0.45	0.46	0.48	0.50	0.51	0.53
2	0.44	0.45	0.46	0.47	0.48	0.49	0.50	0.52	0.54	0.55	0.57

	H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
	0.5	0.11	0.12	0.13	0.14	0.15	0.16	0.18	0.20	0.22	0.24	0.26
	0.6	0.13	0.14	0.15	0.16	0.17	0.18	0.20	0.21	0.23	0.25	0.27
	0.7	0.14	0.15	0.16	0.17	0.18	0.19	0.21	0.23	0.25	0.27	0.29
	0.8	0.15	0.16	0.17	0.18	0.19	0.20	0.22	0.24	0.26	0.28	0.30
	0.9	0.17	0.18	0.19	0.20	0.21	0.22	0.24	0.25	0.27	0.29	0.31
U	1	0.18	0.19	0.20	0.21	0.22	0.23	0.25	0.27	0.29	0.31	0.33
	1.2	0.21	0.22	0.23	0.24	0.25	0.26	0.28	0.29	0.31	0.33	0.35
	1.4	0.23	0.24	0.25	0.26	0.27	0.28	0.30	0.32	0.34	0.36	0.38
	1.6	0.26	0.27	0.28	0.29	0.30	0.31	0.33	0.35	0.37	0.39	0.41
	1.8	0.29	0.30	0.31	0.32	0.33	0.34	0.36	0.37	0.39	0.41	0.43
	2	0.31	0.32	0.33	0.34	0.35	0.36	0.38	0.40	0.42	0.44	0.46

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.14	0.15	0.16	0.17	0.17	0.18	0.20	0.22	0.24	0.25	0.27
0.6	0.16	0.17	0.18	0.18	0.19	0.20	0.22	0.24	0.25	0.27	0.29
0.7	0.18	0.19	0.19	0.20	0.21	0.22	0.24	0.26	0.27	0.29	0.31
0.8	0.20	0.21	0.21	0.22	0.23	0.24	0.26	0.28	0.29	0.31	0.33
0.9	0.22	0.22	0.23	0.24	0.25	0.26	0.28	0.29	0.31	0.33	0.35
1	0.23	0.24	0.25	0.26	0.27	0.28	0.30	0.31	0.33	0.35	0.37
1.2	0.27	0.28	0.29	0.30	0.31	0.32	0.33	0.35	0.37	0.39	0.40
1.4	0.31	0.32	0.33	0.34	0.35	0.36	0.37	0.39	0.41	0.42	0.44
1.6	0.35	0.36	0.37	0.38	0.38	0.39	0.41	0.43	0.45	0.46	0.48
1.8	0.39	0.40	0.41	0.41	0.42	0.43	0.45	0.47	0.48	0.50	0.52
2	0.43	0.44	0.44	0.45	0.46	0.47	0.49	0.50	0.52	0.54	0.56

Late

T (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.24	0.25	0.26	0.27	0.28	0.29	0.31	0.34	0.36	0.38	0.40
0.6	0.28	0.29	0.30	0.31	0.32	0.33	0.35	0.37	0.39	0.41	0.44
0.7	0.32	0.33	0.34	0.35	0.36	0.37	0.39	0.41	0.43	0.45	0.47
0.8	0.36	0.37	0.38	0.39	0.40	0.41	0.43	0.45	0.47	0.49	0.51
0.9	0.39	0.40	0.41	0.42	0.43	0.45	0.47	0.49	0.51	0.53	0.55
1	0.43	0.44	0.45	0.46	0.47	0.48	0.50	0.52	0.55	0.57	0.59
1.2	0.51	0.52	0.53	0.54	0.55	0.56	0.58	0.60	0.62	0.64	0.66
1.4	0.58	0.59	0.60	0.61	0.62	0.63	0.66	0.68	0.70	0.72	0.74
1.6	0.66	0.67	0.68	0.69	0.70	0.71	0.73	0.75	0.77	0.79	0.81
1.8	0.73	0.74	0.75	0.77	0.78	0.79	0.81	0.83	0.85	0.87	0.89
2	0.81	0.82	0.83	0.84	0.85	0.86	0.88	0.90	0.92	0.95	0.97

Q (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.14	0.14	0.15	0.15	0.15	0.16	0.16	0.17	0.17	0.18	0.18
0.6	0.17	0.17	0.17	0.18	0.18	0.18	0.19	0.19	0.20	0.20	0.21
0.7	0.19	0.20	0.20	0.20	0.20	0.21	0.21	0.22	0.22	0.23	0.23
0.8	0.22	0.22	0.23	0.23	0.23	0.23	0.24	0.24	0.25	0.25	0.26
0.9	0.25	0.25	0.25	0.25	0.26	0.26	0.26	0.27	0.27	0.28	0.28
1	0.27	0.27	0.28	0.28	0.28	0.28	0.29	0.30	0.30	0.31	0.31
1.2	0.32	0.33	0.33	0.33	0.33	0.34	0.34	0.35	0.35	0.36	0.36
1.4	0.38	0.38	0.38	0.38	0.39	0.39	0.39	0.40	0.40	0.41	0.41
1.6	0.43	0.43	0.43	0.44	0.44	0.44	0.45	0.45	0.46	0.46	0.47
1.8	0.48	0.48	0.48	0.49	0.49	0.49	0.50	0.50	0.51	0.51	0.52
2	0.53	0.53	0.54	0.54	0.54	0.54	0.55	0.55	0.56	0.56	0.57

T+Q (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.15	0.16	0.17	0.17	0.18	0.19	0.20	0.21	0.23	0.24	0.25
0.6	0.18	0.18	0.19	0.20	0.20	0.21	0.22	0.24	0.25	0.26	0.28
0.7	0.20	0.21	0.21	0.22	0.23	0.23	0.25	0.26	0.27	0.29	0.30
0.8	0.22	0.23	0.24	0.24	0.25	0.26	0.27	0.28	0.30	0.31	0.33
0.9	0.25	0.25	0.26	0.27	0.27	0.28	0.29	0.31	0.32	0.34	0.35
1	0.27	0.28	0.28	0.29	0.30	0.30	0.32	0.33	0.34	0.36	0.37
1.2	0.32	0.32	0.33	0.34	0.34	0.35	0.36	0.38	0.39	0.41	0.42
1.4	0.36	0.37	0.38	0.38	0.39	0.40	0.41	0.43	0.44	0.45	0.47
1.6	0.41	0.42	0.42	0.43	0.44	0.45	0.46	0.47	0.49	0.50	0.51
1.8	0.46	0.46	0.47	0.48	0.49	0.49	0.51	0.52	0.53	0.55	0.56
2	0.50	0.51	0.52	0.53	0.53	0.54	0.55	0.57	0.58	0.59	0.61

R (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.11	0.13	0.14	0.16	0.18	0.19	0.22	0.25	0.28	0.31	0.34
0.6	0.12	0.14	0.15	0.17	0.18	0.20	0.23	0.26	0.29	0.32	0.35
0.7	0.13	0.14	0.16	0.18	0.19	0.21	0.24	0.27	0.30	0.33	0.36
0.8	0.14	0.15	0.17	0.18	0.20	0.21	0.24	0.27	0.31	0.34	0.37
0.9	0.14	0.16	0.17	0.19	0.21	0.22	0.25	0.28	0.31	0.34	0.37
1	0.15	0.17	0.18	0.20	0.21	0.23	0.26	0.29	0.32	0.35	0.38
1.2	0.17	0.18	0.20	0.21	0.23	0.24	0.27	0.30	0.34	0.37	0.40
1.4	0.18	0.20	0.21	0.23	0.24	0.26	0.29	0.32	0.35	0.38	0.41
1.6	0.20	0.21	0.23	0.24	0.26	0.27	0.30	0.33	0.37	0.40	0.43
1.8	0.21	0.23	0.24	0.26	0.27	0.29	0.32	0.35	0.38	0.41	0.44
2	0.23	0.24	0.26	0.27	0.29	0.30	0.33	0.36	0.40	0.43	0.46

H (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.15	0.17	0.20	0.22	0.25	0.27	0.32	0.37	0.42	0.47	0.52
0.6	0.15	0.18	0.20	0.23	0.25	0.28	0.33	0.38	0.42	0.47	0.52
0.7	0.16	0.18	0.21	0.23	0.26	0.28	0.33	0.38	0.43	0.48	0.53
0.8	0.16	0.19	0.21	0.24	0.26	0.29	0.33	0.38	0.43	0.48	0.53
0.9	0.17	0.19	0.22	0.24	0.27	0.29	0.34	0.39	0.44	0.49	0.54
1	0.17	0.20	0.22	0.24	0.27	0.29	0.34	0.39	0.44	0.49	0.54
1.2	0.18	0.20	0.23	0.25	0.28	0.30	0.35	0.40	0.45	0.50	0.55
1.4	0.19	0.21	0.24	0.26	0.29	0.31	0.36	0.41	0.46	0.51	0.56
1.6	0.20	0.22	0.25	0.27	0.30	0.32	0.37	0.42	0.47	0.52	0.57
1.8	0.21	0.23	0.26	0.28	0.31	0.33	0.38	0.43	0.48	0.53	0.58
2	0.22	0.24	0.27	0.29	0.32	0.34	0.39	0.44	0.49	0.54	0.59

NMA (U \ O)	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
0.6	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
0.7	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39
0.8	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
0.9	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
1	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
1.2	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
1.4	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78	0.78
1.6	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
1.8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12

Additional Cost

These tables below show the additional forecast cost of each model for each of the four run-timing groups for each asymmetric loss function examined relative to the best performing model for the given *O*:*U* ratio. Cells that are colored indicate that for a given *O*:*U* ratio the model performed best, while grey cells indicate for that given *O*:*U* ratio that the model performed second best. Each panel in a table corresponds to a model, which is indicated by capital letters in the top-left corner of each table and where T = temperature model , Q = discharge model, T+Q = temperature-plus-discharge model, R = run-timing model, H = historic model, and NMA = no management adjustment model. Historic model = , Temperature model = , Discharge model = , Temperature-plus-discharge model = , Run-timing model = . For example, in the top-left table, which is for the T model, there are only six *O*:*U* ratios (pink cells) for Early Stuart in which that T model is top ranked, whereas the Q model (top-right table) is best (blue cells) in cases of *O*:*U* ratios in the top-right corner.

Early Stuart

O

T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	4%	0%	1%	3%	5%	7%	10%	13%	15%	17%	19%
0.6	8%	4%	0%	0%	2%	3%	7%	9%	12%	14%	16%
0.7	11%	7%	4%	1%	0%	1%	4%	7%	9%	11%	13%
0.8	14%	10%	7%	4%	1%	0%	2%	4%	7%	9%	11%
0.9	17%	13%	9%	6%	4%	1%	0%	2%	5%	7%	8%
1	19%	15%	12%	9%	6%	4%	0%	1%	3%	5%	7%
1.2	23%	19%	16%	13%	10%	8%	4%	0%	0%	2%	3%
1.4	26%	22%	19%	16%	14%	11%	7%	4%	1%	0%	1%
1.6	29%	25%	22%	19%	17%	14%	10%	7%	4%	1%	0%
1.8	31%	27%	24%	22%	19%	17%	13%	9%	6%	4%	1%
2	33%	29%	26%	24%	21%	19%	15%	12%	9%	6%	4%

O

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	8%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.6	15%	8%	2%	0%	0%	0%	0%	0%	0%	0%	0%
0.7	21%	14%	8%	3%	1%	0%	0%	0%	0%	0%	0%
0.8	26%	19%	13%	8%	4%	1%	0%	0%	0%	0%	0%
0.9	30%	23%	17%	12%	8%	4%	0%	0%	0%	0%	0%
1	34%	27%	21%	16%	12%	8%	2%	0%	0%	0%	0%
1.2	40%	34%	28%	23%	19%	15%	8%	2%	0%	0%	0%
1.4	46%	40%	34%	29%	25%	21%	14%	8%	3%	1%	0%
1.6	50%	44%	39%	34%	30%	26%	19%	13%	8%	4%	1%
1.8	54%	48%	43%	38%	34%	30%	23%	17%	12%	8%	4%
2	57%	51%	46%	42%	38%	34%	27%	21%	16%	12%	8%

T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	19%	13%	12%	13%	15%	15%	17%	19%	20%	21%	22%
0.6	25%	19%	13%	12%	13%	14%	15%	17%	18%	19%	20%
0.7	30%	24%	19%	14%	12%	13%	14%	15%	17%	18%	19%
0.8	35%	28%	23%	19%	15%	13%	13%	14%	15%	17%	18%
0.9	39%	33%	27%	23%	19%	15%	12%	13%	14%	15%	16%
1	42%	36%	31%	26%	22%	19%	13%	12%	13%	15%	15%
1.2	48%	42%	37%	33%	28%	25%	19%	13%	12%	13%	14%
1.4	53%	47%	42%	38%	34%	30%	24%	19%	14%	12%	13%
1.6	57%	51%	47%	42%	38%	35%	28%	23%	19%	15%	13%
1.8	60%	55%	50%	46%	42%	39%	33%	27%	23%	19%	15%
2	63%	58%	53%	49%	46%	42%	36%	31%	26%	22%	19%

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	8%	2%	1%	1%	1%	1%	2%	2%	2%	3%	3%
0.6	15%	8%	3%	1%	1%	1%	1%	2%	2%	2%	2%
0.7	21%	14%	8%	3%	1%	1%	1%	1%	2%	2%	2%
0.8	25%	19%	13%	8%	4%	2%	1%	1%	1%	2%	2%
0.9	30%	23%	17%	13%	8%	4%	1%	1%	1%	1%	2%
1	33%	27%	21%	16%	12%	8%	2%	1%	1%	1%	1%
1.2	40%	33%	28%	23%	19%	15%	8%	3%	1%	1%	1%
1.4	45%	39%	33%	29%	24%	21%	14%	8%	3%	1%	1%
1.6	49%	43%	38%	33%	29%	25%	19%	13%	8%	4%	2%
1.8	52%	47%	42%	37%	33%	30%	23%	17%	13%	8%	4%
2	55%	50%	45%	41%	37%	33%	27%	21%	16%	12%	8%

N	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0%	0%	5%	10%	15%	19%	27%	35%	41%	46%	51%
0.6	0%	0%	0%	3%	7%	11%	19%	26%	32%	38%	43%
0.7	0%	0%	0%	0%	2%	5%	13%	19%	25%	31%	35%
0.8	0%	0%	0%	0%	0%	1%	7%	13%	19%	24%	29%
0.9	0%	0%	0%	0%	0%	0%	3%	9%	14%	19%	24%
1	0%	0%	0%	0%	0%	0%	0%	5%	10%	15%	19%
1.2	0%	0%	0%	0%	0%	0%	0%	0%	3%	7%	11%
1.4	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	5%
1.6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
1.8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	147%	123%	111%	103%	95%	88%	76%	65%	55%	47%	39%
0.6	172%	147%	126%	113%	107%	100%	88%	78%	69%	60%	53%
0.7	194%	168%	147%	128%	117%	109%	98%	88%	79%	71%	64%
0.8	213%	187%	165%	147%	131%	119%	107%	97%	88%	80%	73%
0.9	229%	204%	182%	163%	147%	132%	113%	104%	96%	88%	81%
1	243%	218%	197%	178%	161%	147%	123%	111%	103%	95%	88%
1.2	267%	243%	222%	204%	187%	172%	147%	126%	113%	107%	100%
1.4	286%	263%	243%	225%	209%	194%	168%	147%	128%	117%	109%
1.6	302%	280%	261%	243%	227%	213%	187%	165%	147%	131%	119%
1.8	315%	294%	276%	259%	243%	229%	204%	182%	163%	147%	132%
2	326%	307%	289%	272%	257%	243%	218%	197%	178%	161%	147%

Early Summer

T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	12%	9%	6%	4%	2%	1%	0%	0%	0%	0%	0%
0.6	15%	12%	9%	7%	5%	4%	1%	0%	0%	0%	0%
0.7	17%	14%	12%	10%	8%	6%	3%	1%	0%	0%	0%
0.8	22%	16%	14%	12%	10%	8%	5%	3%	1%	0%	0%
0.9	28%	19%	16%	14%	12%	10%	7%	5%	3%	1%	0%
1	33%	24%	17%	15%	14%	12%	9%	6%	4%	2%	1%
1.2	42%	33%	25%	19%	16%	15%	12%	9%	7%	5%	4%
1.4	50%	41%	33%	26%	20%	17%	14%	12%	10%	8%	6%
1.6	57%	48%	40%	33%	27%	22%	16%	14%	12%	10%	8%
1.8	63%	54%	46%	39%	33%	28%	19%	16%	14%	12%	10%
2	68%	59%	51%	44%	38%	33%	24%	17%	15%	14%	12%

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	13%	14%	15%	16%	17%	18%	21%	25%	28%	31%	34%
0.6	12%	13%	14%	15%	16%	16%	18%	21%	24%	27%	29%
0.7	12%	13%	13%	14%	15%	16%	17%	18%	20%	23%	26%
0.8	13%	12%	13%	13%	14%	15%	16%	17%	18%	20%	22%
0.9	17%	12%	12%	13%	13%	14%	15%	16%	17%	18%	19%
1	20%	15%	11%	12%	13%	13%	14%	15%	16%	17%	18%
1.2	25%	20%	15%	12%	12%	12%	13%	14%	15%	16%	16%
1.4	30%	24%	20%	16%	13%	12%	13%	13%	14%	15%	16%
1.6	33%	28%	24%	20%	16%	13%	12%	13%	13%	14%	15%
1.8	37%	32%	27%	23%	20%	17%	12%	12%	13%	13%	14%
2	40%	34%	30%	26%	23%	20%	15%	11%	12%	13%	13%

T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0%	0%	0%	0%	0%	0%	2%	5%	7%	9%	10%
0.6	0%	0%	0%	0%	0%	0%	0%	2%	4%	6%	8%
0.7	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%	5%
0.8	2%	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%
0.9	6%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
1	9%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.2	15%	9%	4%	0%	0%	0%	0%	0%	0%	0%	0%
1.4	20%	14%	9%	5%	2%	0%	0%	0%	0%	0%	0%
1.6	24%	18%	13%	9%	6%	2%	0%	0%	0%	0%	0%
1.8	27%	22%	17%	13%	9%	6%	0%	0%	0%	0%	0%
2	30%	25%	20%	16%	12%	9%	4%	0%	0%	0%	0%

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	25%	25%	25%	25%	25%	25%	28%	32%	34%	37%	39%
0.6	24%	25%	25%	25%	25%	25%	25%	28%	30%	33%	35%
0.7	24%	24%	25%	25%	25%	25%	25%	25%	27%	30%	32%
0.8	27%	24%	25%	25%	25%	25%	25%	25%	25%	27%	29%
0.9	31%	25%	24%	25%	25%	25%	25%	25%	25%	25%	27%
1	35%	29%	24%	24%	25%	25%	25%	25%	25%	25%	25%
1.2	42%	35%	30%	25%	24%	24%	25%	25%	25%	25%	25%
1.4	48%	41%	35%	30%	26%	24%	24%	25%	25%	25%	25%
1.6	53%	46%	40%	35%	31%	27%	24%	25%	25%	25%	25%
1.8	57%	51%	45%	40%	35%	31%	25%	24%	25%	25%	25%
2	61%	54%	49%	44%	39%	35%	29%	24%	24%	25%	25%

H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	12%	18%	23%	28%	32%	35%	45%	53%	61%	67%	73%
0.6	6%	12%	17%	22%	26%	29%	35%	43%	50%	57%	63%
0.7	2%	7%	12%	17%	21%	24%	30%	35%	42%	48%	54%
0.8	0%	3%	8%	12%	16%	20%	26%	31%	35%	41%	47%
0.9	0%	0%	4%	8%	12%	16%	22%	27%	32%	35%	40%
1	0%	0%	1%	5%	9%	12%	18%	23%	28%	32%	35%
1.2	0%	0%	0%	0%	3%	6%	12%	17%	22%	26%	29%
1.4	0%	0%	0%	0%	0%	2%	7%	12%	17%	21%	24%
1.6	0%	0%	0%	0%	0%	0%	3%	8%	12%	16%	20%
1.8	0%	0%	0%	0%	0%	0%	0%	4%	8%	12%	16%
2	0%	0%	0%	0%	0%	0%	0%	1%	5%	9%	12%

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	84%	72%	62%	53%	45%	38%	29%	22%	16%	11%	6%
0.6	96%	84%	74%	65%	57%	50%	38%	30%	24%	19%	14%
0.7	105%	94%	84%	76%	68%	60%	48%	38%	31%	26%	21%
0.8	118%	103%	93%	84%	77%	69%	57%	47%	38%	32%	27%
0.9	133%	110%	100%	92%	84%	77%	65%	55%	46%	38%	32%
1	146%	123%	107%	99%	91%	84%	72%	62%	53%	45%	38%
1.2	169%	146%	127%	110%	103%	96%	84%	74%	65%	57%	50%
1.4	188%	165%	146%	129%	115%	105%	94%	84%	76%	68%	60%
1.6	205%	182%	163%	146%	131%	118%	103%	93%	84%	77%	69%
1.8	219%	197%	178%	161%	146%	133%	110%	100%	92%	84%	77%
2	232%	210%	191%	174%	159%	146%	123%	107%	99%	91%	84%

Summer

O

U

T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	12%	11%	11%	11%	10%	10%	9%	9%	8%	8%	8%
0.6	13%	12%	12%	11%	11%	10%	10%	9%	9%	8%	8%
0.7	13%	12%	12%	12%	11%	11%	10%	10%	9%	9%	9%
0.8	13%	13%	12%	12%	12%	11%	11%	10%	10%	9%	9%
0.9	14%	13%	13%	12%	12%	12%	11%	11%	10%	10%	9%
1	14%	13%	13%	13%	12%	12%	11%	11%	11%	10%	10%
1.2	14%	14%	13%	13%	13%	13%	12%	12%	11%	11%	10%
1.4	14%	14%	14%	14%	13%	13%	12%	12%	12%	11%	11%
1.6	15%	14%	14%	14%	14%	13%	13%	12%	12%	12%	11%
1.8	15%	15%	14%	14%	14%	14%	13%	13%	12%	12%	12%
2	15%	15%	14%	14%	14%	14%	13%	13%	13%	12%	12%

O

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	38%	39%	40%	41%	41%	42%	43%	44%	45%	46%	46%
0.6	37%	38%	39%	40%	40%	41%	42%	43%	44%	45%	45%
0.7	36%	37%	38%	39%	39%	40%	41%	42%	43%	44%	44%
0.8	36%	37%	37%	38%	39%	39%	40%	41%	42%	43%	43%
0.9	35%	36%	37%	37%	38%	39%	40%	41%	41%	42%	43%
1	35%	36%	36%	37%	37%	38%	39%	40%	41%	41%	42%
1.2	34%	35%	35%	36%	37%	37%	38%	39%	40%	40%	41%
1.4	34%	34%	35%	35%	36%	36%	37%	38%	39%	39%	40%
1.6	33%	34%	34%	35%	35%	36%	37%	37%	38%	39%	39%
1.8	33%	33%	34%	34%	35%	35%	36%	37%	37%	38%	39%
2	33%	33%	34%	34%	34%	35%	36%	36%	37%	37%	38%

U

T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.7	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
0.9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	79%	78%	77%	76%	75%	75%	74%	73%	72%	71%	71%
0.6	80%	79%	78%	77%	76%	76%	75%	74%	73%	72%	72%
0.7	80%	79%	79%	78%	77%	77%	76%	75%	74%	73%	73%
0.8	81%	80%	79%	79%	78%	78%	76%	76%	75%	74%	73%
0.9	81%	81%	80%	79%	79%	78%	77%	76%	75%	75%	74%
1	82%	81%	80%	80%	79%	79%	78%	77%	76%	75%	75%
1.2	82%	82%	81%	81%	80%	80%	79%	78%	77%	76%	76%
1.4	83%	82%	82%	81%	81%	80%	79%	79%	78%	77%	77%
1.6	83%	83%	82%	82%	81%	81%	80%	79%	79%	78%	78%
1.8	84%	83%	83%	82%	82%	81%	81%	80%	79%	79%	78%
2	84%	83%	83%	83%	82%	82%	81%	80%	80%	79%	79%

U

H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	44%	46%	48%	50%	52%	54%	56%	59%	61%	62%	64%
0.6	41%	44%	46%	48%	49%	51%	54%	56%	58%	60%	61%
0.7	40%	42%	44%	46%	47%	49%	51%	54%	56%	57%	59%
0.8	38%	40%	42%	44%	45%	47%	49%	52%	54%	55%	57%
0.9	37%	39%	41%	42%	44%	45%	48%	50%	52%	54%	55%
1	36%	38%	39%	41%	42%	44%	46%	48%	50%	52%	54%
1.2	34%	36%	37%	39%	40%	41%	44%	46%	48%	49%	51%
1.4	33%	35%	36%	37%	38%	40%	42%	44%	46%	47%	49%
1.6	32%	33%	35%	36%	37%	38%	40%	42%	44%	45%	47%
1.8	31%	33%	34%	35%	36%	37%	39%	41%	42%	44%	45%
2	31%	32%	33%	34%	35%	36%	38%	39%	41%	42%	44%

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	75%	74%	74%	73%	73%	73%	72%	72%	71%	71%	71%
0.6	75%	75%	74%	74%	73%	73%	73%	72%	72%	71%	71%
0.7	75%	75%	75%	74%	74%	74%	73%	73%	72%	72%	72%
0.8	76%	75%	75%	75%	74%	74%	73%	73%	73%	72%	72%
0.9	76%	75%	75%	75%	75%	74%	74%	73%	73%	73%	72%
1	76%	76%	75%	75%	75%	75%	74%	74%	73%	73%	73%
1.2	76%	76%	76%	75%	75%	75%	75%	74%	74%	73%	73%
1.4	77%	76%	76%	76%	76%	75%	75%	75%	74%	74%	74%
1.6	77%	77%	76%	76%	76%	76%	75%	75%	75%	74%	74%
1.8	77%	77%	77%	76%	76%	76%	75%	75%	75%	75%	74%
2	77%	77%	77%	76%	76%	76%	76%	75%	75%	75%	75%

Late

O

U

T	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	112%	94%	81%	82%	85%	89%	96%	103%	109%	114%	120%
0.6	130%	112%	97%	85%	80%	83%	89%	95%	100%	106%	111%
0.7	146%	127%	112%	99%	88%	79%	84%	89%	94%	99%	103%
0.8	160%	141%	125%	112%	100%	91%	80%	85%	89%	93%	98%
0.9	173%	153%	137%	123%	112%	102%	85%	81%	85%	89%	93%
1	185%	165%	148%	134%	122%	112%	94%	81%	82%	85%	89%
1.2	205%	185%	168%	153%	141%	130%	112%	97%	85%	80%	83%
1.4	221%	202%	185%	170%	157%	146%	127%	112%	99%	88%	79%
1.6	236%	216%	199%	185%	172%	160%	141%	125%	112%	100%	91%
1.8	253%	229%	212%	198%	185%	173%	153%	137%	123%	112%	102%
2	273%	240%	224%	209%	196%	185%	165%	148%	134%	122%	112%

O

Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	25%	12%	2%	0%	0%	0%	0%	0%	0%	0%	0%
0.6	38%	25%	14%	5%	0%	0%	0%	0%	0%	0%	0%
0.7	50%	36%	25%	15%	7%	1%	0%	0%	0%	0%	0%
0.8	61%	47%	35%	25%	16%	9%	0%	0%	0%	0%	0%
0.9	71%	56%	44%	33%	25%	17%	5%	0%	0%	0%	0%
1	80%	65%	52%	42%	33%	25%	12%	2%	0%	0%	0%
1.2	95%	80%	67%	56%	47%	38%	25%	14%	5%	0%	0%
1.4	107%	92%	80%	69%	59%	50%	36%	25%	15%	7%	1%
1.6	118%	103%	91%	80%	70%	61%	47%	35%	25%	16%	9%
1.8	131%	113%	100%	89%	80%	71%	56%	44%	33%	25%	17%
2	145%	121%	109%	98%	88%	80%	65%	52%	42%	33%	25%

U

T+Q	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	33%	23%	14%	15%	17%	20%	25%	29%	33%	37%	41%
0.6	44%	33%	24%	17%	14%	16%	20%	24%	28%	31%	34%
0.7	54%	42%	33%	25%	19%	13%	16%	20%	23%	27%	30%
0.8	63%	51%	41%	33%	26%	20%	14%	17%	20%	23%	26%
0.9	71%	59%	49%	40%	33%	27%	17%	14%	17%	20%	23%
1	78%	66%	55%	47%	39%	33%	23%	14%	15%	17%	20%
1.2	90%	78%	68%	59%	51%	44%	33%	24%	17%	14%	16%
1.4	101%	88%	78%	69%	61%	54%	42%	33%	25%	19%	13%
1.6	109%	97%	87%	78%	70%	63%	51%	41%	33%	26%	20%
1.8	120%	105%	95%	86%	78%	71%	59%	49%	40%	33%	27%
2	133%	112%	102%	93%	85%	78%	66%	55%	47%	39%	33%

R	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	0%	0%	0%	7%	15%	23%	38%	53%	66%	79%	91%
0.6	0%	0%	0%	0%	3%	10%	23%	36%	48%	59%	70%
0.7	0%	0%	0%	0%	0%	0%	12%	23%	34%	45%	55%
0.8	0%	0%	0%	0%	0%	0%	3%	13%	23%	33%	42%
0.9	0%	0%	0%	0%	0%	0%	0%	5%	14%	23%	32%
1	0%	0%	0%	0%	0%	0%	0%	0%	7%	15%	23%
1.2	0%	0%	0%	0%	0%	0%	0%	0%	0%	3%	10%
1.4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1.8	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

U

H	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	29%	33%	36%	48%	61%	75%	100%	124%	146%	167%	187%
0.6	25%	29%	32%	35%	41%	52%	75%	96%	116%	135%	153%
0.7	21%	26%	29%	32%	34%	36%	56%	75%	93%	110%	127%
0.8	18%	22%	26%	29%	32%	34%	41%	58%	75%	91%	106%
0.9	15%	20%	23%	26%	29%	31%	35%	45%	60%	75%	89%
1	13%	17%	21%	24%	27%	29%	33%	36%	48%	61%	75%
1.2	8%	13%	16%	20%	22%	25%	29%	32%	35%	41%	52%
1.4	4%	9%	13%	16%	19%	21%	26%	29%	32%	34%	36%
1.6	1%	6%	9%	13%	16%	18%	22%	26%	29%	32%	34%
1.8	0%	3%	6%	10%	13%	15%	20%	23%	26%	29%	31%
2	0%	0%	4%	7%	10%	13%	17%	21%	24%	27%	29%

NMA	0.5	0.6	0.7	0.8	0.9	1	1.2	1.4	1.6	1.8	2
0.5	144%	115%	93%	86%	83%	80%	74%	69%	63%	59%	54%
0.6	175%	144%	120%	100%	87%	85%	80%	75%	70%	66%	62%
0.7	203%	170%	144%	123%	105%	90%	84%	80%	76%	72%	68%
0.8	227%	194%	167%	144%	125%	109%	87%	84%	80%	76%	73%
0.9	249%	215%	187%	164%	144%	127%	100%	87%	83%	80%	76%
1	269%	235%	206%	182%	162%	144%	115%	93%	86%	83%	80%
1.2	303%	269%	240%	215%	194%	175%	144%	120%	100%	87%	85%
1.4	331%	297%	269%	244%	222%	203%	170%	144%	123%	105%	90%
1.6	355%	322%	294%	269%	247%	227%	194%	167%	144%	125%	109%
1.8	383%	344%	316%	291%	269%	249%	215%	187%	164%	144%	127%
2	414%	363%	335%	310%	288%	269%	235%	206%	182%	162%	144%

Appendix 5: Data

These are the raw data used for this research. Cycle year is the year in the four-year sockeye salmon life-history cycle. Note that this value is not always sequential in the table due to years without data. SE is the spawning escapement. PSE is the potential spawning escapement (Mission abundance minus in-river catch). *D50* is the date at which 50% of a run-timing group reaches Hells Gate. *Q* is the average discharge during the 31-day period centered around *D50* in cubic meters per second. *T* is the average temperature during the 31-day period centered around *D50* in degrees Celsius.

Early Stuart

Year	Cycle year	*SE*	*PSE*	*SE-PSE*	*SE/PSE*	*ln(SE/PSE)*	*D50*	*Q* (m^3/s)	*T* (°C)
1978	2	50	85	-35	0.59	-0.53	8-Jul	4985	16.4
1979	3	93	148	-55	0.63	-0.47	9-Jul	5263	15.1
1981	1	138	200	-62	0.69	-0.37	12-Jul	4961	15.7
1983	3	24	52	-28	0.46	-0.77	12-Jul	5305	15.3
1985	1	238	222	16	1.07	0.07	16-Jul	4646	16.3
1987	3	148	154	-6	0.96	-0.04	16-Jul	4070	17.5
1988	0	180	166	14	1.08	0.08	12-Jul	4705	16.0
1989	1	385	275	110	1.40	0.34	11-Jul	4271	16.8
1990	2	97	116	-19	0.84	-0.18	15-Jul	6386	16.7
1991	3	141	192	-51	0.73	-0.31	21-Jul	5765	16.9
1992	0	66	179	-113	0.37	-1.00	18-Jul	3725	18.6
1993	1	688	490	198	1.40	0.34	19-Jul	3480	17.2
1994	2	29	158	-129	0.18	-1.70	16-Jul	5204	16.7
1995	3	123	166	-43	0.74	-0.30	12-Jul	4142	17.3
1996	0	88	128	-40	0.69	-0.38	15-Jul	6445	15.3
1997	1	267	900	-633	0.30	-1.22	22-Jul	7046	15.8
1998	2	33	169	-136	0.20	-1.63	13-Jul	3993	18.6
1999	3	25	145	-120	0.17	-1.76	14-Jul	8786	13.8
2000	0	90	152	-62	0.59	-0.52	8-Jul	6809	14.7
2001	1	171	205	-34	0.83	-0.18	10-Jul	5149	16.0
2002	2	25	57	-32	0.44	-0.82	15-Jul	6915	15.7
2003	3	13	29	-16	0.45	-0.80	15-Jul	4491	17.1
2004	0	9	96	-87	0.09	-2.37	16-Jul	3858	18.5
2005	1	99	199	-100	0.50	-0.70	27-Jul	4266	17.3
2006	2	36	46	-10	0.78	-0.25	18-Jul	3669	18.5
2007	3	5	12	-7	0.42	-0.88	12-Jul	6817	16.0

Early Summer

Year	Cycle year	*SE*	*PSE*	*SE-PSE*	*SE/PSE*	*ln(SE/PSE)*	*D50*	*Q* (m^3/s)	*T* (°C)
1977	1	46	69	-23	0.67	-0.41	2-Aug	4393	17.0
1978	2	77	76	1	1.01	0.01	10-Aug	3225	17.9
1979	3	168	233	-65	0.72	-0.33	6-Aug	3155	18.0
1980	0	60	87	-27	0.69	-0.37	4-Aug	3142	17.0
1981	1	60	63	-3	0.95	-0.05	1-Aug	4395	18.2
1982	2	91	110	-19	0.83	-0.19	12-Aug	5196	16.8
1983	3	86	181	-95	0.48	-0.74	8-Aug	4101	17.6
1984	0	109	92	17	1.18	0.17	27-Jul	5532	16.1
1985	1	42	34	8	1.24	0.21	7-Aug	3240	17.5
1986	2	196	180	16	1.09	0.09	11-Aug	3563	17.1
1987	3	186	328	-142	0.57	-0.57	6-Aug	3331	17.2
1988	0	180	439	-259	0.41	-0.89	8-Aug	3299	17.8
1989	1	47	97	-50	0.48	-0.73	31-Jul	3548	17.5
1990	2	429	561	-132	0.76	-0.27	15-Aug	3414	19.4
1991	3	248	449	-201	0.55	-0.59	9-Aug	4691	18.2
1992	0	93	145	-52	0.64	-0.44	4-Aug	3016	19.7
1994	2	239	380	-141	0.63	-0.46	9-Aug	3400	19.2
1995	3	154	137	17	1.12	0.12	11-Aug	3739	16.5
1996	0	313	368	-55	0.85	-0.16	2-Aug	4976	16.7
1997	1	53	108	-55	0.49	-0.71	4-Aug	5725	17.0
1998	2	150	418	-268	0.36	-1.03	6-Aug	3118	19.9
1999	3	69	266	-197	0.26	-1.35	5-Aug	6411	16.4
2000	0	532	464	68	1.15	0.14	29-Jul	5474	17.2
2001	1	170	207	-37	0.82	-0.20	28-Jul	5096	16.5
2002	2	367	446	-79	0.82	-0.20	8-Aug	3681	16.8
2003	3	115	193	-78	0.60	-0.52	9-Aug	3079	19.2
2004	0	89	498	-409	0.18	-1.72	5-Aug	2902	20.1
2005	1	163	417	-254	0.39	-0.94	3-Sep	2167	16.3
2006	2	353	969	-616	0.36	-1.01	19-Aug	2026	18.3
2007	3	81	104	-23	0.78	-0.25	16-Aug	3513	17.4

Summer

Year	Cycle year	*SE*	*PSE*	*SE-PSE*	*SE/PSE*	*ln(SE/PSE)*	*D50*	*Q* (m^3/s)	*T* (°C)
1977	1	737	662	75	1.11	0.11	3-Aug	4346	17.1
1978	2	227	263	-36	0.86	-0.15	18-Aug	2885	17.2
1979	3	582	593	-11	0.98	-0.02	14-Aug	2685	18.3
1980	0	571	613	-42	0.93	-0.07	15-Aug	2741	16.5
1981	1	1055	1205	-150	0.88	-0.13	8-Aug	4114	18.7
1982	2	376	353	23	1.07	0.06	14-Aug	5013	16.7
1983	3	510	338	172	1.51	0.41	14-Aug	3615	17.7
1984	0	643	798	-155	0.81	-0.22	13-Aug	4004	17.3
1985	1	1738	1635	103	1.06	0.06	18-Aug	2678	16.9
1986	2	581	752	-171	0.77	-0.26	16-Aug	3217	17.5
1987	3	659	398	261	1.66	0.50	18-Aug	2886	16.7
1988	0	745	346	399	2.15	0.77	17-Aug	2980	17.9
1989	1	2557	2558	-1	1.00	0.00	21-Aug	3021	16.9
1990	2	1597	1911	-314	0.84	-0.18	23-Aug	2884	18.9
1991	3	1257	1178	79	1.07	0.07	24-Aug	4200	17.3
1992	0	635	867	-232	0.73	-0.31	20-Aug	2378	18.6
1993	1	5072	3920	1152	1.29	0.26	31-Aug	2378	17.4
1994	2	1323	1872	-549	0.71	-0.35	16-Aug	2896	18.8
1995	3	918	985	-67	0.93	-0.07	14-Aug	3650	16.3
1996	0	1411	1129	282	1.25	0.22	13-Aug	4012	17.1
1997	1	3807	3894	-87	0.98	-0.02	26-Aug	3603	17.4
1998	2	2382	3936	-1554	0.61	-0.50	19-Aug	2526	19.1
1999	3	1281	1493	-212	0.86	-0.15	17-Aug	5148	17.0
2000	0	1650	1058	592	1.56	0.44	13-Aug	3978	17.6
2001	1	4684	3749	935	1.25	0.22	19-Aug	3705	17.3
2003	3	1002	1277	-275	0.78	-0.24	22-Aug	2415	18.4
2004	0	273	898	-625	0.30	-1.19	15-Aug	2559	19.8
2005	1	2455	3886	-1431	0.63	-0.46	4-Sep	2147	16.2
2006	2	815	1152	-337	0.71	-0.35	21-Aug	1942	18.3
2007	3	431	483	-52	0.89	-0.11	16-Aug	3513	17.4

Late

Year	Cycle year	*SE*	*PSE*	*SE-PSE*	*SE/PSE*	*ln(SE/PSE)*	*D50*	*Q* (m^3/s)	*T* (°C)
1978	2	2008	1832	176	1.10	0.09	28-Sep	2404	12.6
1982	2	3404	3419	-15	1.00	0.00	1-Oct	2750	
1986	2	2483	3355	-872	0.74	-0.30	27-Sep	1578	13.5
1990	2	3760	3003	757	1.25	0.23	25-Sep	1612	16.5
1994	2	1459	910	549	1.60	0.47	29-Sep	1534	15.7
1996	0	105	367	-262	0.29	-1.25	9-Sep	2814	15.2
1997	1	38	71	-33	0.54	-0.63	16-Sep	2486	15.5
1998	2	1478	2836	-1358	0.52	-0.65	18-Sep	1427	16.3
1999	3	406	957	-551	0.42	-0.86	14-Sep	2769	14.7
2000	0	15	339	-324	0.04	-3.12	18-Aug	3572	17.3
2001	1	44	375	-331	0.12	-2.14	25-Aug	3272	17.1
2002	2	5693	6217	-524	0.92	-0.09	17-Sep	2330	14.3
2003	3	446	640	-194	0.70	-0.36	1-Sep	1953	17.5
2004	0	32	178	-146	0.18	-1.72	25-Aug	2670	18.6
2006	2	3128	4897	-1769	0.64	-0.45	10-Sep	1377	16.5
2007	3	229	451	-222	0.51	-0.68	23-Aug	2991	17.1