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Optimal Inseason Management of Pink Salmon Given Uncertain Run Sizes and Declining Economic Value

A

THESIS

Presented to the Faculty
of the University of Alaska Fairbanks

in Partial Fulfillment of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

By

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Juneau, Alaska

December 2001

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Abstract

This is a comprehensive study on the fishery and management system (including the inseason stock abundance dynamics, the purse seine fleet dynamics and the inseason management) of pink salmon (*Oncorhynchus gorbuscha*) in the northern Southeast Alaska (NSE) inside waters.

Firstly, we presented a new and improved methodology, a hierarchical Bayesian modelling approach (HBM), for estimating salmon escapement abundance and timing from stream count data, which improves estimates in years when data are sparse by "borrowing strength" from counts in other years. We presented a model of escapement and of count data, a hierarchical Bayesian statistical framework, a Gibbs sampling estimation approach for posterior distributions, and model determination techniques. We then applied the HBM to estimating historical escapement parameters for pink salmon returns to Kadashan Creek in Southeast Alaska.

Secondly, a simulation study was conducted to compare the performance of the HBM to that of separate maximum likelihood estimation of each year's escapement. We found that the HBM was much better able to estimate escapement parameters in years where few or no counts are made after the peak of escapement. Separate estimates for such years could be wildly inaccurate. However, even a single postpeak count could dramatically improve the estimability of escapement parameters.

Third, we defined major stocks and their migratory pathways for the NSE pink salmon. We estimated the escapement timing parameters of these stocks by the HBM. A boxcar migration model was then used to reconstruct the catch and abundance histories for these stocks from 1977 to 1998.

Finally, we developed a stochastic simulation model that simulates this fishery and management system. Uncertainties in annual stock size and run timing, fleet dynamics and both preseason and inseason forecasts were accounted for explicitly in this simulation. The simulation model was applied to evaluating four kinds of management strategies with different fishing opening schedules and decision rules. When only flesh quality is concerned, the present and a more aggressive strategy, both of which are adaptive to the run strength of the stocks, are able to provide higher quality fish without compromising the escapement objectives.

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Foreword

Introduction

This project is a comprehensive study on the escapement process, migration and inseason abundance dynamics of pink salmon stocks, and on the fleet dynamics and inseason management of pink salmon fisheries in the northern Southeast Alaska (NSE). The ultimate objective is to build a model that simulates this complex fishery and inseason management system, thus providing a tool to evaluate alternative inseason management strategies with specific management objectives.

Southeast Alaska (SEAK) is a narrow strip of land between the Gulf of Alaska and the Coast Range Mountains (Fig. I). This region comprises numerous large and small islands known as the Alexander Archipelago. It is one of the most productive areas in the world for five Pacific salmon species due to its diverse geographical conditions, heavy forest and abundant rainfall. Pink salmon is the most abundant salmon species in this region. It is the target species of the purse seine fishery, which takes about 90% of the pink salmon caught.

The SEAK pink salmon fisheries have been the subject of numerous past investigations. Tagging studies have attempted to define stocks, clarify migratory pathways, and estimate the interception rates of Canadian fish (e.g., Nakatani et al. 1975; Hoffman 1982; Hoffman et al. 1986). An extensive discussion of stock structure and the history of the fishery can be found in Alexandersdottir (1987). Much effort has been put into forecasting the abundance of the run, both before the season (Mathisen and Van Alen 1995; Courtney 1997; Adkison and Mathisen 1997) as well as within the fishing season (McKinstry 1993; Zheng and Mathisen 1998). Efforts have also been made to uncover the factors influencing variability in run strength (Hofmeister 1994; Jaenicke 1995). The economics of the fishery and the impact of management on the economics of the fishery have received less attention.

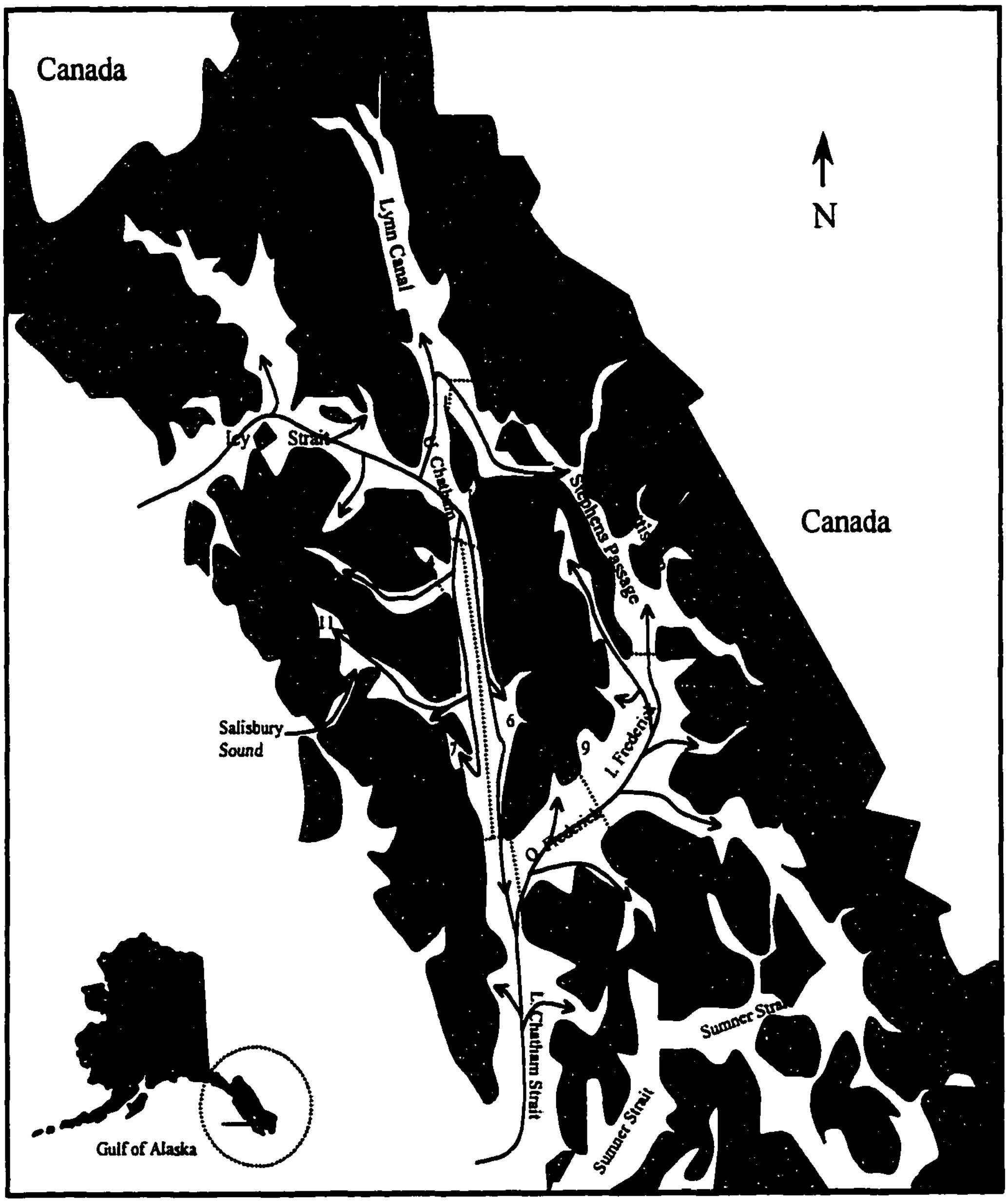

Fig. I. Northern Southeast Alaska.

The curves and arrows show the pathways and directions of the migration of pink salmon in this region. 1—Hawk Inlet, 2—Howard Bay, 3—Point Augusta, 4—Freshwater Bay, 5—Kadashan Creek, 6 – Chaik Bay, 7—Kelp Bay, 8—Point Gardner, 9—Pybus Bay, 10—Kingsmill Point, 11—Hoonah Sound.

Motivation and objectives

This project is motivated by the flesh quality (thus the commercial value) issue of pink salmon in this region. Record salmon harvests in Alaska combined with increasing supplies of farmed salmon have reduced the value of salmon in general (Knapp 1992). The market for pink salmon has been particularly affected, in part because of record supplies and in part because pink salmon is one of the least-preferred species. In recent years, processors have been unwilling to purchase all of the pink salmon that could have been caught, and in particular declined to purchase fish with low flesh quality (Ben Van Alen, ADF&G, Juneau, AK pers. comm.). Thus how to avoid harvesting of poor flesh quality fish and how to promote the harvest of high-quality fish becomes a major concern of the local fishery industry and managers.

Stock conservation and flesh-quality promotion are the two most important but conflicting objectives for the management of pink salmon in this region. The flesh quality of pink salmon deteriorates with the progress of the season (Chapter 4). The quality and commercial value of pink salmon fishery are maximized by harvesting earlier in the season, and in offshore districts farthest from the spawning grounds. However, to ensure conservation the opposite strategy is optimal. It is safer to start harvesting fish late in the season in order to allow adequate escapement (to withstand the uncertainties in run strength). The more outside mixed-stock areas are avoided where stock-specific harvest rates are hard to apply, thus preventing weaker runs suffering from over-harvesting. The objective of this study is aimed at finding the balance point of these two conflicting objectives and identifying management strategies that might potentially increase the economic value of the pink salmon fisheries yet not compromise the conservation goals.

Simulation (or preseason planning) models are often used to examine alternative harvesting strategies to achieve specific management objectives for salmon fishery management studies (Walters and Buckingham 1975; Starr and Hilborn 1988; Cave and Gazey 1994). We use simulation techniques to evaluate the effects of various management strategies on the performance of pink salmon stocks and their fisheries in NSE Alaska.

The target system of the simulation

The fishery and inseason management system of NSE pink salmon includes three major components: the stocks, fishing fleet and inseason management. These components are interactive. The abundance dynamics of the stocks are determined by three processes: entry, migration and escapement. The managers make decisions on the timing, duration and distribution of the fishery openings to regulate the fishing fleet indirectly in order to achieve specific escapement goals and other objectives (e.g., orderly harvest and higher product quality). In SEAK, the fishing areas are opened concurrently for each opening, and the fishing vessels can move freely among areas (Van Alen 2000). The movements of fishing vessels among areas at each opening are assumed to be in response to the changes in the abundance of the stocks in these areas (Chapter 4). The fishing vessels in each area at each opening remove a portion of the fish from that area and thus impact the abundance dynamics of related stocks. Finally, the changes in stock abundance affect the managers' decisions about future fishing openings.

The inputs to the system are the daily numbers of fish entering the inside waters of NSE, and the fishery openings and the number of boats operating at each open time and place. The outputs are the daily catch and escapement. Fishing opening is the control variable, regulated by managers to achieve various escapement and harvest objectives. This system is a typical stochastic system. The run size and timing, migration routes, and escapement of each stock vary annually. The fleet dynamics component is particular variable because of the complex and variable decision-making process of the fishermen (Hilborn 1985). This is reflected in the large amount of annual variation in the number of fishing boats present in a specific open area in this region (see Table 4.1). The relationship between harvest rate and the number of boats fishing, which ties the stock and fishing fleet components together, is also subject to a large amount of uncertainty because of the variation in the intensity and efficiency of the fishing boats (see Table 4.2). The inseason decision-making of the managers that is based on these uncertain states of the stocks and fishing fleet is also subject to a lot of uncertainty.

System analysis and simulation—the contents of the project

Our simulation model is a necessary simplification of this complex stochastic system. All of the primary processes and relationships are modeled, including the three stock dynamics processes, the relationships between the stocks and fleet, and the inseason management process. We use stochastic equations or randomly-drawn samples to model those stochastic processes.

A major characteristic of a simulation model is that all the relationships are supposed to be known to us, including the functional forms and the parameters of these relationships. Given these equations, we can vary controllable inputs, run the simulation model, and examine the effects of these inputs on the outputs (performance). This means that running the simulation model is the simplest task of a simulation study. Before that, one must make great efforts to understand the target system. That is what we have done for this project.

Most of the effort in this project was put into learning the system, including identifying the major components, processes and relationships of the system, determining the optimal functional form that describes a relationship (model selection) and estimate the parameters of that relationship (estimation). In each of Chapters 1-3 and part of Chapter 4, we modeled and estimated one or more components of the target system.

In Chapters 1 and 2, we made a thorough study of the escapement process and provided a new and improved methodology, a Bayesian hierarchical modeling (HBM) approach, for the estimation of salmon escapement abundance and timing from escapement survey count data.

In Chapter 1, we presented a model of escapement and of count data, a hierarchical Bayesian statistical framework, a Gibbs sampling approach for evaluation of the posterior distributions of the quantities of interest, and criteria for determining when the model and inference are adequate. We then applied the HBM to estimating historical escapement and escapement timing for pink salmon returns to Kadashan Creek in Southeast Alaska.

In Chapter 2, we compared the performance of the HBM approach to that of separate maximum likelihood estimation of each year's escapement. We simulated several contrasting counting schedules, resulting in data sets that differed in information content. We found that the HBM approach was much better able to estimate escapement and escapement timing in years where few or no counts are made after the peak of escapement. Separate estimates for such years could be wildly inaccurate. However, even a single postpeak count could dramatically improve the estimability of escapement parameters.

Chapters 1 and 2 were published in the August 2001 issue of the Canadian Journal of Fisheries and Aquatic Sciences.

In Chapter 3, we conducted an analysis of the stock component to provide the biological basis for the management simulation in the following chapter. We defined stocks and their migratory pathways. The escapement timing of each stock was estimated using the HBM approach of Chapter 1. Finally, run reconstruction techniques were applied to estimate the inseason abundance histories of these stocks (Starr and Hilborn 1988; Templin et al. 1996).

In Chapter 4, we modeled the fleet dynamics of the NSE purse seine fisheries and the relationship of harvest rate versus the number of fishing boats of each fishery. We also described the management strategy applied to pink salmon in this region.

This chapter included designing the simulation method that ties all the component models together, determining alternative management strategies and their evaluation criteria, model verification and validation, and conducting the simulation. The simulation model was applied to evaluating four kinds of management strategies with different fishing opening schedules and decision rules. The principal result was that both the current strategy and a more aggressive strategy, as long as they adapted themselves to the run strength, were able to provide higher value fish without compromising the escapement objectives.

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Chapter 1. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing[1]

Abstract

In this chapter, we present a new and improved methodology for estimating salmon escapements from stream count data. The new method uses a hierarchical Bayesian model (HBM) that improves estimates in years when data are sparse by "borrowing strength" from counts in other years. We present a model of escapement and of count data, a hierarchical Bayesian statistical framework, a Gibbs sampling approach for evaluation of the posterior distributions of the quantities of interest, and criteria for determining when the model and inference are adequate. We then apply the HBM to estimating historical escapement and escapement timing for pink salmon (*Oncorhynchus gorbuscha*) returns to Kadashan Creek in Southeast Alaska.

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[1] An earlier version of this chapter is published as Su, Zhenming, Adkison, Milo D., and Van Alen, Benjamin W. 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. Can. J. Fish. Aquat. Sci. 58: 1648-1662.

Introduction

Escapement data are essential for salmon population conservation and management (Quinn and Deriso 1999). In North America, most escapement data are obtained by aerial or foot escapement surveys (Cousens et al. 1982) in which fish observed in a stream are enumerated at several occasions to obtain a series of counts. Each count is just an estimate of the actual number of spawners in a stream at the time of the survey, not the total escapement (some fish will have died before counting and some will not yet have entered). Thus, some method must be used to convert these counts to escapement. Usually escapement is estimated with the "area-under-the-curve" method (English et al. 1992; Hilborn et al. 1999), a somewhat ad hoc calculation that uses the counts in conjunction with an estimate of the average longevity of spawners (stream life) (Perrin and Irvine 1990; Fukushima and Smoker 1997). More recently, statistical models have been developed to estimate escapement from escapement counts. Quinn and Gates (1997) developed a biologically detailed stream escapement model to estimate salmon escapement dynamics. Hilborn et al. (1999) provided a maximum likelihood method to estimate stream escapement using a simpler model. In addition to providing an estimate of the total escapement, these statistical methods can estimate escapement timing as well. Escapement timing information is an important prerequisite for run reconstruction techniques (Starr and Hilborn 1988; Chapter 3).

For these modeling approaches, separately estimating the escapement in each year may be adequate for years with informative data (Quinn and Gates 1997; Hilborn et al. 1999). However, in some years counts may be sparse and insufficient to provide reliable estimates. Even with a large number of survey counts, estimation can easily fail due to a lack of data for the last half of the run (Hilborn et al. 1999). Area-under-the-curve estimates are even more affected by such holes in the data, as part of the curve is missing. Such deficiencies are common in historical data; weather, manpower shortages or budget difficulties may limit counts, and managers often discontinue counts once escapement goals are met.

Hilborn et al. (1999) proposed using prior information on run timing to constrain the escapement model when data for a particular year were uninformative. Such information is most logically derived from the escapement timing of the stock in other years. The timing of salmon returning to a particular stream is remarkably consistent from year to year (Heard 1991), so historical data may contain strong prior information on escapement timing in the current year. One could specify prior distributions for escapement timing parameters from this historical information, and perform a Bayesian or even a maximum likelihood analysis separately for each year of data (Hilborn et al. 1999). A more formal statistical methodology, hierarchical modeling (Lindley and Smith 1972; Gelman et al. 1995), exists that would allow estimation for all years simultaneously, "borrowing strength" from years with informative data to improve estimates for years with uninformative data.

Hierarchical modeling has many applications in biology, medicine, economics, etc. (Davidian and Giltinan 1995; Gelman et al. 1995). It is also naturally applied in meta-analysis where studies have to be pooled together (Mosteller and Chalmers 1992; see Liermann and Hilborn 1997 for a fisheries example). Hierarchical models (HMs) assume dependence among parameters, with parameters in lower levels regarded as samples drawn from higher-level population distributions.

Compared with non-hierarchical approaches, one advantage of HMs is that they make full use of all the data available and can estimate parameters at all levels simultaneously. Another advantage of hierarchical modeling is that it saves degrees of freedom by structuring some dependence among the parameters, reducing the effective number of parameters and thereby avoiding problems of overfitting that are often suffered by non-hierarchical models (Gelman et al. 1995). Bayesian (Carlin and Louis 1996; Gelman et al. 1995) and traditional maximum likelihood procedures (Davidian and Giltinan 1995) can both be applied for the fitting of HMs, although Bayesian approach provides more accurate assessments for uncertainty in parameters (Browne and Draper 2000).

In this paper, we develop a statistical escapement estimation methodology using hierarchical Bayesian modeling (HBM). The hierarchical component is the assumption that the timing of escapement in each year is a sample drawn from a stock-specific distribution of possible timings. This assumption enables us to use all of the historical survey data for a stream to improve escapement estimates for years with uninformative data, as well as to make inferences about typical escapement characteristics of the stream.

We also incorporate an additional improvement over past escapement estimation practices. Traditional methods, such as the "area-under-the-curve" method and Hilborn et al.'s (1999) model, used an average stream life to convert counts to escapement. However, it is well known that longevity of salmon on the spawning ground declines as the season progresses (Dangel and Jones 1988; Perrin and Irvine 1990; Fukushima and Smoker 1997), so using an average stream life may bias the estimation. Our spawning abundance model incorporates a stream life that declines as the season progresses.

The article is organized as follows. First we describe a salmon spawning abundance model. We then develop a HBM that combines counts for all the years together. A hybrid Metropolis-Gibbs algorithm is used for fitting the HBM (Appendix A). We derive the full conditional distributions needed for this approach. We demonstrate a whole set of Bayesian methodologies for high-dimensional Bayesian model fitting through Markov chain Monte Carlo (MCMC) techniques (Gilks et al. 1996), detailed convergence diagnostics of MCMC (Appendix B), and Bayesian model checking and comparison (Appendix C). Finally, we apply the HBM approach to escapement estimation for a pink salmon (*Oncorhynchus gorbuscha*) stock in Southeast Alaska.

Models and methods

A salmon spawning abundance model

There are two processes determining the dynamics of salmon spawning abundance in a stream during the spawning season: entry and mortality. Let η_t denote the number of spawners at the beginning of day t, x_t be the number of spawners entering the stream during day t, and d_t be the number of fish that die in the same period, then the spawning abundance is:

$$(1.1)\quad \eta_{t+1} = \eta_t + x_t - d_t = \sum_{k=1}^{t} x_k - \sum_{k=1}^{t} d_k$$

with an initial condition $\eta_{T_1} = 0$ at the starting day T_1 of the stream entry.

Weir studies show that salmon escapement timing can be asymmetric, with pulses of stream entry. With infrequent stream counts it is usually intractable to estimate these irregular features of stream entry. To some extent, these irregularities in entry are smoothed in taking stream counts by the overlap of fish that arrived on multiple days. In our model, the daily entry of salmon into the stream is approximated by a normal curve:

$$(1.2)\quad x_t = Ee^{-(t-M)^2/(2S^2)}/\Psi$$

where E denotes the total escapement, M denotes the mean date of arrival and S denotes the standard deviation of the dates of arrival (i.e., the duration of the run). The value

$$\Psi = \sum\nolimits_{t=T_1}^{T_2} e^{-(t-M)^2/(2S^2)}$$

is a normalizing constant ensuring that

$$\sum\nolimits_{t=T_1}^{T_2} (e^{-(t-M)^2/(2S^2)}/\Psi) = 1$$

so that daily entry takes certain percentage of the total escapement. The value T_2 represents the last day of the stream entry.

We add one level of biological realism not usually incorporated in escapement models. Let $l(t)$ be the stream life of the fish entering in day t. It is known that $l(t)$ is a declining function of date within the spawning season (Dangel and Jones 1988; Perrin and Irvine 1990; Fukushima and Smoker 1997). Here we use an exponential equation to express the stream life by date of entry:

$$(1.3) \quad l(t)=\phi_1 e^{-\phi_2(t-M)}$$

where ϕ_1 and ϕ_2 are two shape parameters estimated separately from independent stream life surveys and M is the mean date of arrival. The uncertainty in these two parameters is briefly considered in a sensitivity analysis (see "An application, Stream life estimates" section below).

In our model, we assume that fish entering the stream on day ξ die $l(\xi)$ days later:

$$(1.4.1) \quad \delta_{\xi+l(\xi)} = x_\xi = Ee^{-(\xi-M)^2/(2S^2)}/\Psi$$

where $\delta_{\xi+l(\xi)}$ denotes the number of those fish that enter the stream in day ξ and die afterward in day $\xi+l(\xi)$. Due to the declining nature of our stream life function, it is possible that on some day fish from several different entry days might die (this is not the case for a constant stream life where each entry day is mapped to a unique mortality day). We express the actual number of fish that died on day t as sum over stream entry days:

$$(1.4.2) \quad d_t=\sum_{\{\xi\}}\delta_{\xi+l(\xi)} \quad \text{with } \xi\in\{\xi:\xi+l(\xi)=t\}$$

Thus the spawning abundance can be expressed as

$$(1.5) \quad \eta_t=\sum_{k=1}^{t}x_k-\sum_{k=1}^{t}d_k$$

$$= \sum_{k=1}^{t} x_k - \sum_{k=1}^{t} \sum_{\{\xi\}} \delta_{\xi+l(\xi)}$$

$$= E\left(\sum_{k=1}^{t} e^{-(k-M)^2/(2S^2)} - \sum_{k=1}^{t} \sum_{\{\xi\}} e^{-(\xi-M)^2/(2S^2)} \right) / \Psi$$

$$= E\Phi_t$$

where

$$\Phi_t = \left(\sum_{k=1}^{t} e^{-(k-M)^2/(2S^2)} - \sum_{k=1}^{t} \sum_{\{\xi\}} e^{-(\xi-M)^2/(2S^2)} \right) / \Psi,$$

the proportion of the total escapement alive in the stream in day t.

Let c_t denote the observed stream count in day t. We assume a normally distributed measurement error in the counts. Thus, we have:

$$(1.6) \quad c_t = \eta_t + \varepsilon_t$$

where $\varepsilon_t \sim N(0, \sigma^2)$. Whenever necessary, the counts are transformed to meet the previous normal model assumptions (see "A hierarchical methodology, The hierarchical model" below).

Separate estimation for each year

Given particular values of M, S, and E, the model equations above can be used to predict the number of fish in the stream on any date (η_t). Where we employed separate estimation below, maximum likelihood parameter estimates (MLEs) for a particular year were estimated using a nonlinear search algorithm that selected candidate values of *M*, *S*, and *E* to minimize SSQ, where SSQ was the following:

$$(1.7)\quad \mathrm{SSQ} = \sum_{\{t\}} \left(c_t - \eta_t(M,S,E)\right)^2$$

The estimate of σ^2 was calculated as SSQ/(No. of counts – No. of parameters).

Confidence intervals for each parameter were obtained by a bootstrap approach. In each bootstrap trial, residuals from the MLE fit were randomly sampled with replacement and added to the predicted counts to create a pseudo-data set. MLEs for these pseudo-data were then calculated. This bootstrap was repeated 3000 times (the percentiles became stable after about 500 iterations), and then the resulting estimates were ordered by size. Finally, the 2.5th and 97.5th percentiles were taken as the lower and upper bounds of the 95% confidence interval.

A hierarchical Bayesian methodology

The hierarchical model

Suppose that we have *Y* years of survey data for a stream. For year *y*, there are n_y counts. Let $c_{y,t}$ denote the observed count on survey day *t* for year *y*, M_y, S_y and E_y denote the three unknown escapement parameters for year *y*, and σ^2 denotes the data error variance. As in Eq. 1.6, we have a model for the (possibly transformed) $c_{y,t}$ as

$$(1.8)\quad c_{y,t} \mid \theta_y, \sigma^2 \overset{indep}{\sim} N(\eta_{y,t}, \sigma^2), y = 1, \ldots, Y$$

where $\theta_y = (M_y, S_y, E_y)$. In this model, we allow for the possibility of a different timing and escapement in each year but assume a homogeneous measurement error for all years.

The hierarchical component of the model is the assumption that the timing of escapement is similar from year to year (Heard 1991). We express both the similarity and heterogeneity of escapement timing by assuming that the M_y and $\ln(S_y)$ are drawn from the following distributions:

$$(1.9)\quad M_y \mid \mu_m, \tau_m^2 \overset{iid}{\sim} N(\mu_m, \tau_m^2)$$

$$\ln(S_y) \mid \mu_s, \tau_s^2 \overset{iid}{\sim} N(\mu_s, \tau_s^2)$$

where μ_m, μ_s are population mean parameters, and τ_m^2, τ_s^2 are population variance parameters. Preliminary analysis of stream escapement data in our study area leads us to assume that M_y and $\ln(S_y)$ are independent of each other. Because of the high variability in abundance from year to year, we do not impose a hierarchical structure on the E_y's. Eqs. 1.8 and 1.9 form a two stage hierarchical model. There are in total $3Y+5$ unknown parameters for this model, which are $\theta = (\{\theta_y\}, \sigma^2)$ (here θ_y is redefined as the set $(M_y, \ln(S_y), E_y)$, and $y = 1,\ldots, Y$), and four hyperparameters $\lambda = (\mu_m, \tau_m^2, \mu_s, \tau_s^2)$.

For the purpose of simplicity, the error in counts is assumed to have the same variance (σ^2) for all years. However, annual escapements often fluctuate by many orders of magnitude. To achieve common measurement error variances, we could scale the observed counts for each year by dividing by the peak count $c_{y,p}$ (labeled *scaling*). This is equivalent to setting $\sigma_y = \sigma c_{y,p}$, but keeps our model in a simple form. Square root transformation (SQRT) (Quinn and Gates 1997) of the counts was also considered and its performance was compared with *scaling* (we also explored a logarithm transformation (Hilborn et al. 1999)).

We denote the previous model the M_y-S_y model. Two more parsimonious models can be derived from the M_y-S_y model: (*i*) the M_y-S model with $\ln(S_y) = \ln(S)$ and parameters $\theta = (\{M_y, E_y\}, \ln(S), \sigma^2)$ and $\lambda = (\mu_m, \tau_m^2)$, and (*ii*) the M-S$_y$ model with $M_y = M$ and parameters $\theta = (M, \{\ln(S_y), E_y\}, \sigma^2)$ and $\lambda = (\mu_s, \tau_s^2)$. We consider both the M$_y$-S model and M-S$_y$ model as alternatives, with *scaling* and SQRT as two data transformation options, but continue to focus on the more general M$_y$-S$_y$ model in the narrative.

Prior specification

A full Bayesian analysis requires specifying prior distributions for the hyper-parameters $\lambda = (\mu_m, \tau_m^2, \mu_s, \tau_s^2)$ and the data-level parameters $\{E_y\}$ and σ^2. We assume prior independence for all these parameters. The prior specifications form the third stage of the HBM.

For μ_m and μ_s, we set their priors as $\mu_m \sim N(a_m, V_m)$ and $\mu_s \sim N(a_s, V_s)$, where $a_m, V_m, a_s,$ and V_s are constants to be specified by the modelers. Choosing large V_m and V_s will make these two prior distributions relatively uninformative but still proper (Spiegelhalter et al. 1997) (a proper prior is a prior density, say, $p(\vartheta)$, that can integrate to one (or any positive finite value), i.e., the integral $\int p(\vartheta)d\vartheta$ is a constant).

The specification of the priors of the population variance parameters (e.g. τ_m^2 and τ_s^2) needs special treatment in a HBM, because an automatic use of the standard "uninformative" improper priors (e.g. $p(\sigma^2) \propto 1/\sigma^2$) for these parameters might lead to improper posteriors (Gelman et al. 1995; Hobert and Casella 1996) (for an improper posterior density, say $p(\vartheta \mid y)$, the integral $\int p(\vartheta \mid y)d\vartheta$ is not finite for all *y*). The safest way to get around this problem is by specifying proper prior distributions for these parameters. We set the priors for τ_m^2 and τ_s^2 as inverse gamma distributions (*IG*) (see Gelman et al. 1995): $\tau_m^2 \sim IG(c_m, d_m)$ and $\tau_s^2 \sim IG(c_s, d_s)$, respectively. To obtain uninformative priors for these hyper-variance parameters, we set $c = d = \varepsilon$, where ε is a small positive value (Spiegelhalter et al. 1997).

For convenience, uninformative priors are specified for the remaining parameters: $E_y \sim U(0,\infty)$, and $\sigma^2 \sim IG(0.001,0.001)$. Similar priors are specified for the M_y-S and M-S_y models.

Combining the priors, population distributions, and likelihood (see Hilborn et al. 1999), we obtain the joint posterior distribution for all the parameters in the M_y-S_y model as

$$(1.10)\quad p(\theta,\lambda \mid D) \propto p(\lambda)p(\sigma^2)\prod_{y=1}^{Y} N(M_y \mid \mu_m,\tau_m^2)$$

$$\times\prod_{y=1}^{Y} N(\ln(S_y) \mid \mu_s,\tau_s^2)\prod_{y=1}^{Y} p(E_y)\prod_{t=1}^{n_y} N(c_{y,t} \mid \eta_{y,t},\sigma^2)$$

where $p(\lambda) = p(\mu_m)p(\tau_m^2)p(\mu_s)p(\tau_s^2)$, and D denotes observed data.

For the M_y-S model, we have

$$(1.11)\quad p(\theta,\lambda \mid D) \propto p(\lambda)p(\ln(S))p(\sigma^2)$$

$$\times\prod_{y=1}^{Y} N(M_y \mid \mu_m,\tau_m^2)\prod_{y=1}^{Y} p(E_y)\prod_{t=1}^{n_y} N(c_{y,t} \mid \eta_{y,t},\sigma^2)$$

where $p(\lambda) = p(\mu_m)p(\tau_m^2)$.

For the M-S_y model, the joint posterior distribution is

$$(1.12)\quad p(\theta,\lambda \mid D) \propto p(\lambda)p(M)p(\sigma^2)$$

$$\times\prod_{y=1}^{Y} N(\ln(S_y)\,|\,\mu_s,\tau_s^2)\prod_{y=1}^{Y} p(E_y)\prod_{t=1}^{n_y} N(c_{y,t}\,|\,\eta_{y,t},\sigma^2)$$

where $p(\lambda) = p(\mu_s)p(\tau_s^2)$.

MCMC: An adaptive hybrid Metropolis-Gibbs sampler

We choose a hybrid MCMC algorithm, the Metropolis-Gibbs sampler (Tierney 1994), to evaluate our complex joint posterior distributions. The hierarchical model structure and our specification of appropriate conjugate priors enabled us to derive full conditional distributions with familiar distributional forms (e.g. normals and inverse gammas) for most of the parameters in our HBM. This allowed use of Gibbs sampling (Geman and Geman 1984; Gelfand and Smith 1990), a means of generating sample values from the joint posterior distribution by sequential draws from the full conditional distributions. Non-standard forms for the distribution of the escapement timing parameters required embedding Metropolis steps within the Gibbs procedure (Tierney 1994; Carlin and Louis 1996).

The Gibbs sampler and the full conditional distributions

The Gibbs sampler generates random draws for all the parameters by sampling successively from the full posterior conditional distribution of each parameter $p(\varphi_i\,|\,\{\varphi_j\}_{j\neq i}, D)$, $i = 1, \ldots, p$, where $\{\varphi_j\}_{j\neq i}$ is the set of all the parameters of a model except for φ_i. Under very broad conditions (Geman and Geman 1984), the Gibbs sampler produces a Markov chain with the joint posterior distribution as its equilibrium distribution. Consequently, the sampled values of φ_i from the Gibbs sampler after convergence can be regarded as random draws obtained from its marginal posterior distribution. Thus simple summary statistics and kernel density estimates based on these draws can be used to summarize the marginal posterior distribution for each parameter.

The full conditional distribution of a parameter is obtained by extracting the terms in the posterior distribution only involving that parameter (its prior and likelihood) and treating all other terms as constants. For example, the terms involving μ_m in Eq. 1.10 are its prior term $p(\mu_m) = N(\mu_m \mid a_m, V_m)$ and its likelihood term

$$\prod_{y=1}^{Y} N(M_y \mid \mu_m, \tau_m^2)$$

The likelihood term, treated as a function of μ_m, can be shown to be $N(\mu_m \mid \hat{\mu}_m, \tau_m^2 / Y)$, where

$$\hat{\mu}_m = \frac{1}{Y} \sum_{y=1}^{Y} M_y$$

Multiplying the likelihood by the prior, we obtain:

$$(1.13)\quad \mu_m \mid \{M_y\}, \tau_m^2 \sim N\left[\frac{a_m \tau_m^2 + Y\hat{\mu}_m V_m}{\tau_m^2 + YV_m}, \frac{V_m \tau_m^2}{\tau_m^2 + YV_m}\right]$$

Similarly, we derived the rest of the full conditionals for the M_y-S_y, M_y-S and M-S_y models and these are listed as follows:

$$(1.14)\quad \tau_m^2 \mid \{M_y\}, \mu_m \sim IG(c_m + Y/2, d_m + Y\hat{\tau}_m{}^2/2)$$

where $\hat{\tau}_m{}^2 = \frac{1}{Y} \sum_{y=1}^{Y} (M_y - \mu_m)^2$

$$(1.15)\quad \mu_s \mid \{\ln(S_y)\}, \tau_s^2 \sim N\left[\frac{a_s\tau_s^2 + Y\hat{\mu}_s V_s}{\tau_s^2 + YV_s}, \frac{V_s\tau_s^2}{\tau_s^2 + YV_s}\right]$$

with $\hat{\mu}_s = \frac{1}{Y}\sum_{y=1}^{Y}\ln(S_y)$

$$(1.16)\quad \tau_s^2 \mid \{\ln(S_y)\}, \mu_s \sim IG(c_s + Y/2, d_s + Y\hat{\tau}_s^2/2)$$

where $\hat{\tau}_s^2 = \frac{1}{Y}\sum_{y=1}^{Y}(\ln(S_y) - \mu_s)^2$

$$(1.17)\quad \sigma^2 \mid \{M_y, \ln(S_y), E_y\} \sim IG(c_1 + n/2, d_1 + n\hat{\sigma}^2/2)$$

where $\hat{\sigma}^2 = \frac{1}{n}\sum_{y=1}^{Y}\sum_{t=1}^{n_y}(c_{y,t} - \eta_{y,t})^2$, and $n = \sum_{y=1}^{Y} n_y$

$$(1.18)\quad E_y \mid M_y, \ln(S_y), \sigma^2 \sim N(\hat{\mu}_{E_y}, V_{E_y})$$

where $\hat{\mu}_{E_y} = \sum_{t=1}^{n_y}(\Phi_{y,t}c_{y,t}) \Big/ \sum_{t=1}^{n_y}(\Phi_{y,t})^2$ and $V_{E_y} = \sigma^2 \Big/ \sum_{t=1}^{n_y}(\Phi_{y,t})^2$

$$(1.19)\quad p(M_y \mid \mu_m, \tau_m^2, \ln(S_y), E_y, \sigma^2) \propto N(\mu_m, \tau_m^2)\exp\left(-\frac{1}{2\sigma^2}\sum_{t=1}^{n_y}(c_{y,t} - \eta_{y,t})^2\right)$$

$$(1.20)\quad p(\ln(S_y) \mid \mu_s, \tau_s^2, M_y, E_y, \sigma^2) \propto N(\mu_s, \tau_s^2)\exp\left(-\frac{1}{2\sigma^2}\sum_{t=1}^{n_y}(c_{y,t} - \eta_{y,t})^2\right)$$

For the M_y-S model, Eqs. 1.15, 1.16, and 1.20 are replaced by:

$$(1.21)\quad p(\ln(S)\,|\,\{M_y, E_y\}, \sigma^2) \propto N(\ln(S)\,|\,a_s, V_s)\exp\left(-\frac{1}{2\sigma^2}\sum_{y=1}^{Y}\sum_{t=1}^{n_y}(c_{y,t}-\eta_{y,t})^2\right)$$

For the M-S_y model, Eqs. 1.13, 1.14, and 1.19 are replaced by:

$$(1.22)\quad p(M\,|\,\{\ln(S_y), E_y\}, \sigma^2) \propto N(M\,|\,a_m, V_m)\exp\left(-\frac{1}{2\sigma^2}\sum_{y=1}^{Y}\sum_{t=1}^{n_y}(c_{y,t}-\eta_{y,t})^2\right)$$

The Metropolis steps

The full conditional distributions for the parameters M_y, $\ln(S_y)$, $\ln(S)$ and M (Eqs. 19-22) are not in closed form due to the nonlinearity of the spawning abundance model. It is not straightforward to generate random values from these distributions. We apply Metropolis steps to sample from each of these conditionals (Carlin and Louis 1996). For more details of the implementation of Metropolis steps, see Appendix A.

In Appendices B and C, we also provide further details for the implementation of the MCMC convergence diagnostics and model comparison and adequacy checking.

An application

Kadashan Creek pink salmon

We applied the HBM to estimate historical pink salmon escapements for Kadashan Creek in Southeast Alaska. Escapement counts for this stream were obtained from the Alaska Department of Fish and Game (ADF&G) Integrated Database (Van Alen 2000). Most of these counts are collected through aerial escapement surveys.

In this paper, we illustrate the results for Kadashan Creek over the period 1974-1998. Escapement counts from this stream vary considerably among years in both

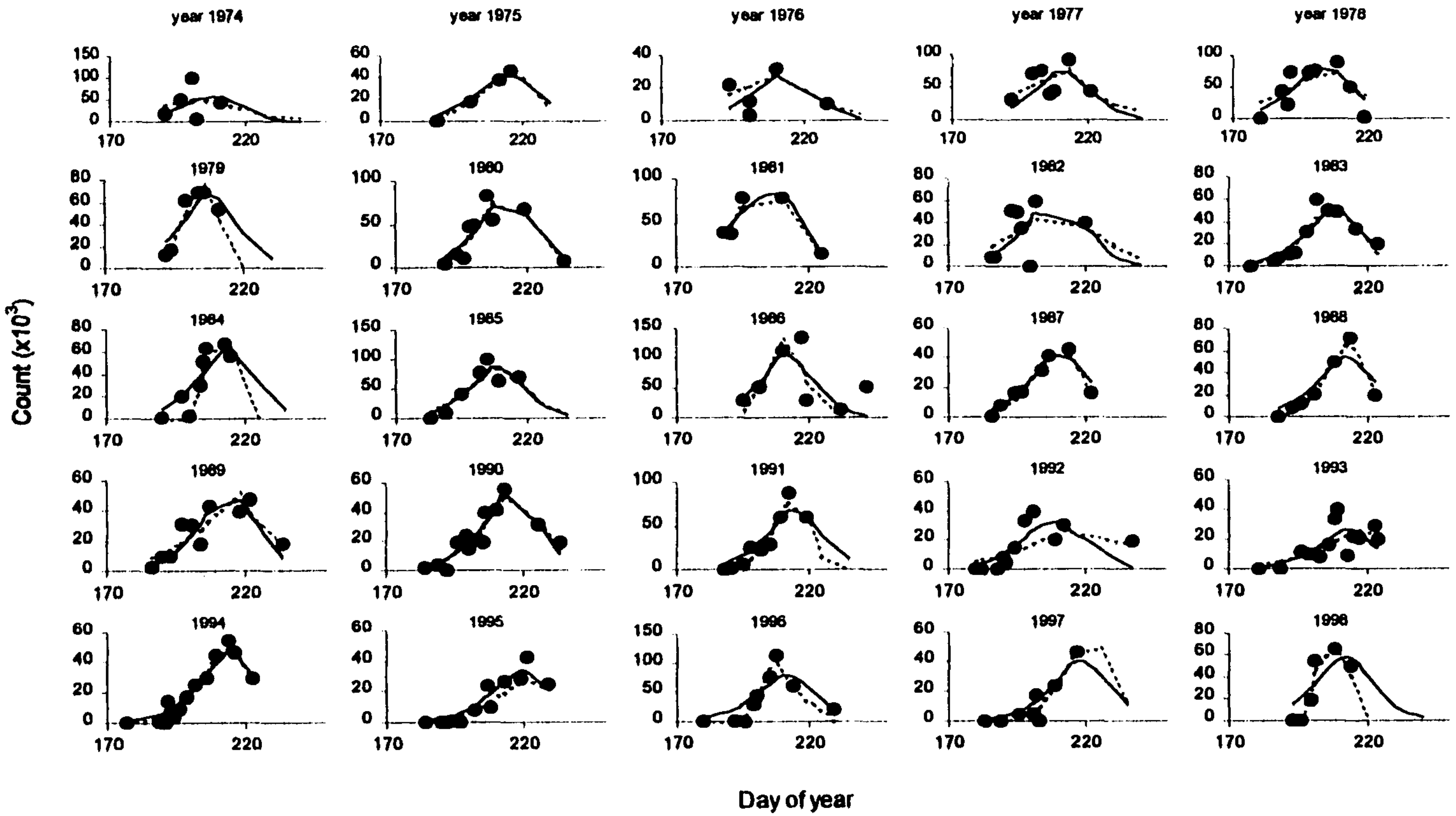

Fig. 1.1 Count data (×1000, circles) and model fits for Kadashan Creek, 1974-1998. The solid line is the fit of the M_y-S model using scaled counts and a non-constant stream life. The dashed line is the fit obtained by separate estimation of each year.

frequency and duration (Fig. 1.1). The scale of the counts also varies by severalfold across years, necessitating transformation of the counts. However, scatter plots of the counts suggest similar run timing among years. Thus, the hierarchical approach seems reasonable for this stock.

Stream life estimates

The relationship between stream life and entry date was estimated outside of the HBM framework. Dangel and Jones (1988) studied stream life of pink salmon spawners in several streams in Southeast Alaska: the Kadashan River in 1986, and Pleasant Bay Creek, Black Bear Creek, and Sashin Creek in 1986 and 1987. We used these data to estimate the decline in stream life with date as follows: first, we centered the stream life values for each stream in each year around the mean date of the corresponding stream entry (obtained from the weir data of Dangel and Jones (1988)). Then we combined the data from all streams (Fig. 1.2), and fitted to the stream life equation, Eq. 1.3. The estimated parameter values were $\hat{\phi}_1 = 14.16$ and $\hat{\phi}_2 = 0.0284$.

The period when Kadashan Creek was surveyed in 1986 was from July 31 to Aug. 10, much shorter than the period of the stream entry (July 18 to Aug. 28). Nevertheless, we fit Eq. 1.3 to the Kadashan data and obtained $\hat{\phi}_1 = 11.8$ and $\hat{\phi}_2 = 0.0078$ (a small declining rate) for this creek. These parameters imply that stream life in Kadashan Creek was approximately constant. We looked at the effect of assuming a constant stream life (set to 11.8 ($\hat{\phi}_1$)) and compared the results using this assumption (referred to as CnSL) to those obtained assuming a declining stream life.

Details of estimation

We estimated escapement, the date of peak escapement, and the standard deviation in date of escapements for historical Kadashan Creek data using the M_Y-S_Y model, M_Y-S model, and M-S_Y models, and separate estimation of each year. A Pascal program running under the Borland Delphi environment was developed to perform all the calculations. We used both the *scaling* and SQRT transformations of count data from

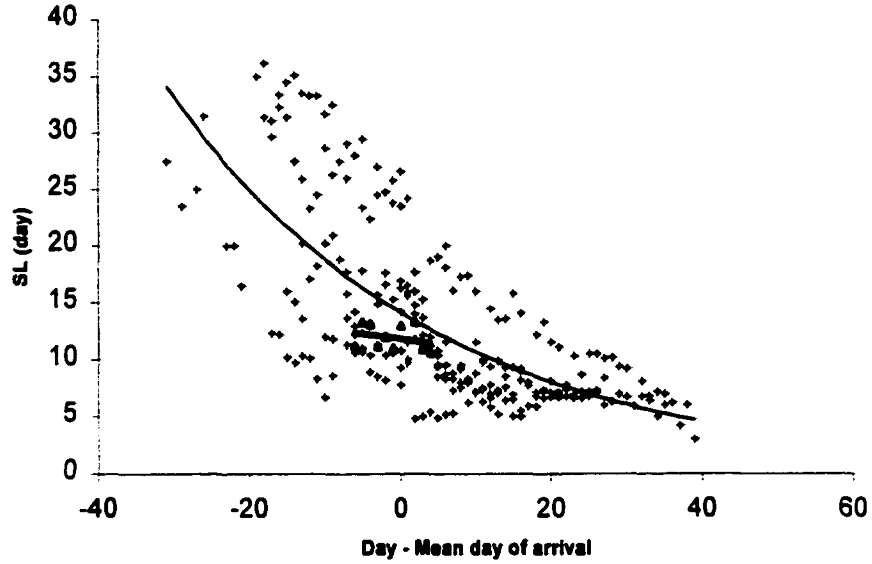

Fig. 1.2 Combined stream life (SL) data and those for Kadashan Creek from Dangel and Jones (1988) and the exponential fitting curves for these two data sets.

Crosses denote combined SL data, and triangles denote SL data for Kadashan creek. The thin line is the fit for combined data and the heavy line for the Kadashan data.

1974 to 1998. Because of convergence problems, some model comparisons were made using only data from 1977-1998 (see "Results" section below).

The data appeared to contain ample information to estimate μ_m, μ_s, the E_y's, and σ^2 (see "Results" section below). We specified uninformative priors for these parameters: $\mu_m \sim N(210, 10^5)$, $\mu_s \sim N(2.5, 10^3)$, $E_y \sim U(0,\infty)$, and $\sigma^2 \sim IG(0.001, 0.001)$.

We set $\tau_m^2 \sim IG(0.001, 0.001)$. The data seemed less informative for the population variance parameters τ_m^2 and τ_s^2 in the M_y-S_y model, especially for the latter (see "Results" section below). Accordingly, we checked the sensitivity of the posterior estimates to the specification of the prior of τ_s^2. Under the *scaling* transformation, we compared the priors $IG(0.01, 0.01)$ and $IG(0.1, 0.1)$. Under the SQRT transformation, we compared the priors $IG(0.001, 0.001)$ and $IG(0.01, 0.01)$.

For the M_y-S model, we set $p(\ln(S)) \propto N(2.5, 10^3)$. For the M-$S_y$ model, we set $p(M) \propto N(210, 10^5)$ and $\tau_s^2 \sim IG(0.001, 0.001)$. Other priors were kept the same as for the M_y-S_y model.

Results

Convergence diagnostics

We first describe in detail the steps taken to assess convergence (Appendix B) for the M_y-S_y model with the *scaling* transformation of the counts. Similar processes were repeated for other models and data transformations.

The MCMC chain did not converge if we used the M_y-S_y model with the complete data set. A fundamental ambiguity existed between τ_m^2 and τ_s^2. The MCMC chain would spend long periods with either τ_m^2 or τ_s^2 at a value of zero, effectively reducing the M_y-S_y model to one of its simpler forms. Using these simpler forms, the M_y-S and M-S_y models, the MCMC chain did converge. The M_y-S_y also converged when the first three years of the data series, which were very uninformative, were discarded.

We ran the Gibbs sampler an initial 3000 iterations to tune the *SD*'s of the proposal distributions used in the Metropolis steps to draw values of M_y and $\ln(S_y)$ so as to obtain an acceptance rate in the range of 40%-60% for each of these parameters (Appendix A). We then ran the Gibbs sampler for an additional 5000 iterations. The results from these 5000 iterations showed that the hyperparameters and the timing parameters had relatively high autocorrelations (lag 1 autocorrelations range from 0.8 ~ 0.9). Their autocorrelation function (acf) decayed slowly, approaching zero only after about lag 15. In contrast, most of the escapement parameters had low autocorrelations.

The Raftery and Lewis convergence diagnostic (Appendix B) indicated that τ_m^2 and τ_s^2 were the slowest to converge, requiring 35 000 iterations in order to get an accuracy for the 2.5th percentiles within ± 0.005 with 95.5% probability.

Due to these autocorrelations, we reran the Gibbs sampler for 200 000 iterations with a thinning interval of 20. This time, all diagnostics were satisfied. We then ran another Gibbs sampler sequence with different starting values, and Gelman and Rubin's diagnostic (Appendix B) indicated convergence of the chains. Thus, the output after convergence was used for subsequent inference.

Model checking and comparison

Table 1.1 shows the values of the coefficients of skewness and kurtosis of the standardized residuals (Appendix C). The values of skewness for all cases is near zero, indicating that the standardized residuals achieve reasonable symmetry in their distributions (Snedecor and Cochran 1982) and implying that the models are neither over-fitted nor under-fitted. The values of the kurtosis indicate possible heavy tails in the distribution, less so with the *scaling* than the SQRT transformation. We also explored a logarithmic data transformation (not shown) and found it to be worse than SQRT. In summary, *scaling* the counts seems slightly more appropriate for this data set than SQRT.

Table 1.1 also reports the values of model comparison quantities (Appendix C). With *scaling*, the M_y-S model has the smallest value of the negative cross-validation log-likelihood (ncvlogL) (Appendix C), indicating that it is preferred. The values of the deviance information criterion, DIC, for the M_y-S_y and M_y-S models are very close, so the M_y-S model would also be the preferred model according to the principle of parsimony. The values of both ncvLogL and DIC indicate that the M-S_y model fit the data less well than the other two models. Under SQRT, the two model comparison criteria favor the M_y-S_y model more than the simpler models. Under both data transformations, the estimated effective number of parameters (p_D) for the M_y-S_y model is in the range of 43~47, versus the nominal value of 71. For the two simpler models, the values of p_D are in the range of 38~41 versus the nominal value of 48.

Table 1.1 Model checking and choice quantities for data from 1977 to 1998.

Measurement		Coefficient of skewness	Kurtosis	ncvLogL	$\overline{D}$	p_D	DIC
Scaling	M_y-S_y[a]	0.138	4.16	-6.3	-86.8	42.8	-43.9
	M_y-S_y[b]	0.108	4.16	-5.3	-87.7	44.6	-43.1
	M_y-S	0.181	4.13	-7.3	-84.2	40.9	-43.3
	M-S_y	0.259	3.31	3.8	-48.3	39.2	-9.1
SQRT	M_y-S_y[c]	-0.385	4.73	1073.5	2076.4	47.0	2123.4
	M_y-S_y[d]	-0.385	4.74	1073.0	2078.6	45.2	2123.8
	M_y-S	-0.189	5.76	1074.6	2097.4	38.2	2135.6
	M-S_y	-0.307	4.20	1078.3	2106.2	41.0	2147.2

Note: ncvLogL $= -\sum \log(\mathrm{cpo}_{y,t})$, the negative cross-validation log-likelihood (Appendix C). The $\overline{D}$ is the posterior mean of deviance, p_D is the effective number of parameters, DIC is the deviance information criterion (Appendix C).

[a] Prior for $\tau_s^2 \sim IG(0.01,0.01)$.

[b] Prior for $\tau_s^2 \sim IG(0.1,0.1)$.

[c] Prior for $\tau_s^2 \sim IG(0.001,0.001)$.

[d] Prior for $\tau_s^2 \sim IG(0.01,0.01)$.

Sensitivity to the prior

Preliminary analyses indicated that τ_s^2 was the parameter most sensitive to prior specifications with the M_y-S_y model. Under *scaling*, with two priors of τ_s^2 ($IG(0.01, 0.01)$ and $IG(0.1, 0.1)$), the posterior medians and 95% credible intervals of τ_s^2 were 0.023 (0.004, 0.127) and 0.069 (0.024, 0.244) respectively (see the values in the bordered area in Table 1.2). The first prior has a peak at 0.0099 and the latter at 0.09, indicating that the priors tended to pull the posteriors towards their modes. Under SQRT transformation, the posteriors of τ_s^2 were not so sensitive, but their left tails seemed to be influenced by the priors. The other parameters were much more robust to their priors, especially the population means and the yearly parameters (Table 1.2).

Table 1.2 Posterior summary for the hyperparameters and annual parameters obtained from the M_y-S_y, M_y-S and M-S_y models under two kinds of data transformations and two stream life models using data from 1977 to 1998.

Data transformation	Model	μ_m (*M*)	τ_m^2	μ_s (ln(*S*))	τ_s^2	σ^2	M_y	ln(S_y)	E_y(x10^3)
Scaling	M_y-S_y[a]	207.7	20.1	2.6	0.023	0.038	207.6	2.6	110.5
		(205.0, 210.9)	(7.5, 48.7)	(2.4, 2.8)	(0.004, 0.127)	(0.03, 0.05)	(10.5)	(0.7)	(68.6)
	M_y-S_y[b]	207.8	18.6	2.6	0.069	0.038	207.7	2.6	110.1
		(205.1, 211.1)	(5.5, 47.0)	(2.4, 2.9)	(0.024, 0.224)	(0.03, 0.05)	(11.3)	(0.9)	(69.4)
	M_y-S	207.7	21.7	2.6	-	0.038	207.6	-	111.4
		(205.2, 210.8)	(10.0, 51.4)	(2.4, 2.8)	-	(0.03, 0.04)	(9.4)	-	(68.0)
	M-S_y	209.6	-	2.8	0.096	0.046	-	2.8	113.3
		(207.7, 212.2)	-	(2.5, 3.0)	(0.028, 0.268)	(0.04, 0.06)	-	(0.8)	(66.6)
	M_y-S_y[c]	206.5	22.5	2.4	0.029	0.035	206.4	2.4	**142.8**
	(CnSL)	(204.1, 209.2)	(10.3, 52.8)	(2.2, 2.5)	(0.005, 0.128)	(0.03, 0.05)	(9.3)	(0.7)	**(102.3)**
SQRT	M_y-S_y[d]	208.3	21.6	2.5	0.049	2123	208.2	2.5	108.6
		(205.7, 211.5)	(6.3, 53.6)	(2.3, 2.7)	(0.002, 0.216)	(1680, 2725)	(11.9)	(0.8)	(105.1)
	M_y-S_y[e]	208.4	21.0	2.5	0.063	2097	208.2	2.5	108.4
		(205.7, 211.5)	(6.3, 54.2)	(2.3, 2.7)	(0.010, 0.236)	(1653, 2706)	(11.9)	(0.8)	(103.1)
	M_y-S	208.4	22.6	2.5	-	2328	208.4	-	108.9
		(205.7, 211.7)	(9.2, 57.1)	(2.4, 2.6)	-	(1874, 2947)	(10.8)	-	(111.0)
	M-S_y	209.2	-	2.6	0.122	2434	-	2.6	108.4
		(207.5, 211.2)	-	(2.4, 2.8)	(0.044, 0.325)	(1964, 3089)	-	(0.8)	(88.3)

Note: For the hyperparameters and σ^2 the median of the posterior distribution is shown with the boundaries of the 95% credible interval below in parentheses. For the annual parameters, the average across years of the posterior median is given with the average width of the 95% credible interval below in parentheses.

[a] Prior for $\tau_s^2 \sim IG(0.01, 0.01)$.

[b] Prior for $\tau_s^2 \sim IG(0.1, 0.1)$.

[c] Assumes stream life is a constant (CnSL) rather than declining with date.

[d] Prior for $\tau_s^2 \sim IG(0.001, 0.001)$.

[e] Prior for $\tau_s^2 \sim IG(0.01, 0.01)$.

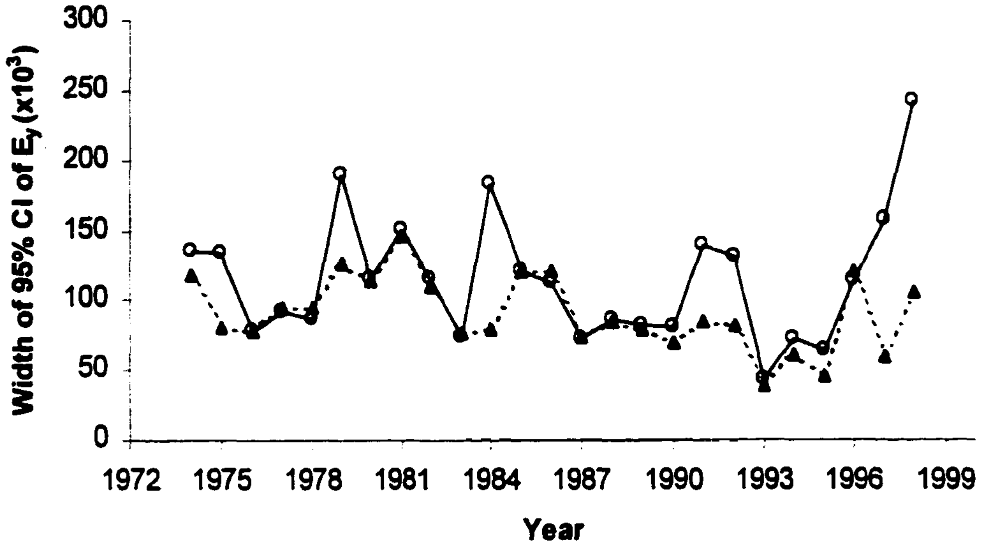

Fig. 1.3 Width of 95% credible interval (CI) for E_y for each year.

Results are shown for the M_y-S and M-S_y models using the SQRT transformation of the counts and a non-constant stream life. The solid line is for the M_y-S and the dashed line is for the M-S_y model.

The 95% credible intervals of E_y were the most sensitive to the data transformation (Table 1.2). *Scaling* produced narrower 95% credible intervals of E_y than SQRT for most years. The SQRT transformation has the property of down-weighting the large counts and up-weighting the small counts. Thus, the tail area of the count curves was fit better than with *scaling*, but fits around the peaks could be quite different. For years 1979, 1984, 1991 and 1998, which are years with a single count shortly after the observed peak, SQRT would quite often treat this count as a value with large observation error rather than a point containing important information about escapement timing. This may be the reason that SQRT produced large variance estimates of escapements for these years.

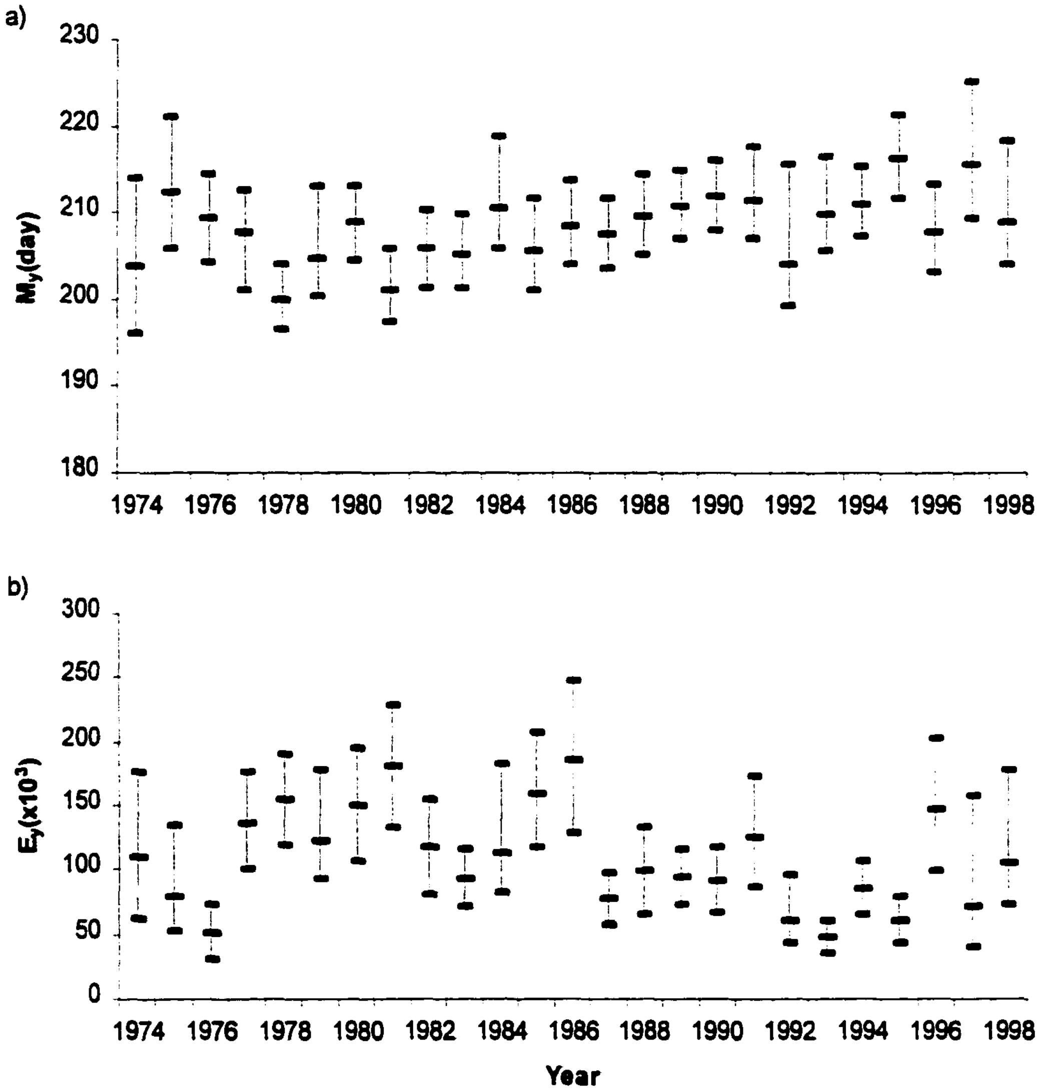

Fig. 1.4 Posterior median and 95% credible interval for M_y (day of year) (a) and E_y (×1000) (b) for each year. Results are shown for the M_y-S model using scaled counts and a non-constant stream life.

The M-S_y model yields narrower 95% credible intervals of E_y than the other two models, especially under SQRT (see bolded values in Table 1.2). By forcing the M_y to a common value, we greatly reduce the uncertainty in E_y for years with little postpeak data (Figs. 1.1 & 1.3).

The posterior distributions of M_y and E_y achieve reasonable symmetry for the informative years (e.g. 1980, 1983, 1989 and 1990 etc.) under both kinds of data transformations (Fig. 1.4). However, posterior distributions of M_y and E_y are positively skewed for years such as 1974, 1975, 1979, 1984, 1991, 1992, 1997 and 1998 (Fig. 1.4), which are years with few or no postpeak counts (Fig. 1.1).

Effects of stream life

Assumptions about stream life appeared very important in determining the magnitude of the escapement estimates and also influenced estimates of variance. Using a constant stream life resulted in posterior medians of the E_y that were bigger and 95% credible intervals that were wider than with a non-constant stream life (see bolded values in the bordered area in Table 1.2). We separately analyzed the effects of the two parameters of our stream life model (Eq. 1.3). For a fixed ϕ_2, the three yearly parameters increase as ϕ_1 decreases. When ϕ_1 is fixed, M_y and S_y decrease and E_y increases as ϕ_2 decreases.

Comparison of the HBM with separate estimation of each year

Table 1.3 compares the posterior estimates obtained from the M_Y-S_Y model with *scaling* to the bootstrap estimates from separate estimation for four representative years. The 1990 data (Fig. 1.1) contain two postpeak counts many days past the peak, and the counts show no apparent pulses. The 1992 data contain three postpeak counts, but have apparent pulses and one possible outlier that result in a large amount of "measurement" error. The 1997 data have no postpeak counts, while the 1998 data have one count shortly after the peak.

In all cases, separate estimates matches the observed count data more closely than the HBM fit, but differ more among years in run timing (Fig. 1.1). Nevertheless, the quality of the separate estimates is more sensitive to that of the data (Table 1.3). Where the data are informative (e.g., 1990), the point estimates (medians) from these two approaches are comparable (Table 1.3); credible intervals using the HBM are wider because the HBM approach considers the properties of other years where counts suggest different run timing. In years where no postpeak counts exist (e.g. 1997) or the data have irregular features (e.g., 1992, 1998 (with an anomalous run timing)), separate estimation is unable to unambiguously determine the run timing (see bolded medians and confidence intervals in Table 1.3) and consequently the escapement, whereas HBM is able to use the shapes of other years' timing curves to narrow the uncertainty considerably.

Table 1.3 Posterior summary (median, and the 95% credible interval below in parentheses) for the annual parameters obtained from a HBM (the M_y-S_y model with *scaling* with priors for $\tau_m^2 \sim IG(0.001,0.001)$, $\tau_s^2 \sim IG(0.01,0.01)$) versus the bootstrap summary statistics (median, and the 95% confidence interval below in parentheses) from separate estimation (SepEst) for four divergent years (see text).

	M_y		S_y		$E_y(\times 10^3)$	
Year	HBM	SepEst	HBM	SepEst	HBM	SepEst
1990	211.3	212.8	13.4	14.7	90.7	97.6
	(207.4, 215.4)	(210.1, 216.6)	(9.9, 18.4)	(11.2, 19.8)	(66.6, 116.1)	(83.9, 111.9)
1992	203.4	226.4	13.9	**35.1**	59.8	76.9
	(198.2, 215.7)	(203.8, **>350.0** [a])	(9.3, 21.0)	(14.4, **>100.0** [b])	(35.9, 93.1)	(37.4, **209.9**)
1997	214.1	216.4	12.1	10.7	68.8	86.5
	(208.2, 222.8)	(207.9, **>350.0** [a])	(7.8, 16.6)	(4.2, 40.1)	(39.7, 142.4)	(43.2, **1.9 x 10^6**)
1998	207.9	200.8	12.8	**1.0**	97.7	66.6
	(202.7, 215.9)	(**200.7**, **200.8**)	(8.3, 18.0)	(**<1.0** [c], 1.9)	(69.6, 152.1)	(60.7, **71.0**)

[a] The value 350.0 is the upper bound of the constraint set for M_y

[b] The value 100.0 is the upper bound of the constraint set for S_y

[c] The value 1.0 is the lower bound of the constraint set for S_y

Simulation studies (Chapter two, Table 2.4) show that the bootstrap confidence intervals from separate estimation underestimate the uncertainty of the parameters, while the HBMs provides approximately correct uncertainty estimates. This may explain some of the instances of seemingly more precise estimates for separate estimation.

Discussion

In this paper, we have extended escapement estimation methods such as the deterministic area-under-the-curve method (English et al. 1992) and statistical modeling of each year separately (Quinn and Gates 1997; Hilborn et al. 1999) to a hierarchical Bayesian paradigm. Methods that treat each year's data separately are prone to failure in years where count data are sparse, particularly if counts are lacking after the peak in escapement (Hilborn et al. 1999; Chapter two). Our HBM approach is able to use historical escapement data for a stream to "borrow strength" from years with good data to obtain improved annual estimates for escapement and its timing in years with poor data.

Our approach also differs from traditional escapement estimation methods in incorporating the well-known decline in longevity on the spawning grounds as the season progresses (Perrin and Irvine 1990). The Kadashan example shows that spawning abundance models are sensitive to assumptions about stream life, in particular in estimating the magnitude of escapement. Since stream life can vary by year as well as by date within a year, this is an important source of error in escapement estimation.

Observer efficiency can be another important factor influencing escapement estimation. It is known that aerial and foot surveys often undercount the number of spawners presented in a stream, especially when the density of the fish is high (Jones et al. 1998). Within- and between-observer variability and bias of counts are also observed (Jones et al. 1998). The pink salmon counts we used here have been partially corrected for bias (Van Alen 2000). Hilborn et al. (1999) suggests that weir studies on index streams should be used to estimate observer bias and stream life.

In our example, we found that appropriate error assumptions for the counts and simplification of the HBM were necessary for convergence of the Gibbs sampler. For example, the Gibbs sampler may fail to converge under the M_y-S_y model setting if the counts are not transformed because the scale of the counts for different years may vary by several orders of magnitude. The *scaling* and SQRT transformations proposed here are both able to address this problem, but the *scaling* transformation seemed to work better in our example. Nevertheless, the difference between SQRT and *scaling* fits in these sorts of cases was smaller than the variability that resulted from using a separate estimation approach, where data from uninformative years didn't constrain escapement timing.

Further refinement of the HBM is possible. Pulsed entry (caused by irregular fishing and variability in the entry process) is typical for salmon escaping to spawning streams. Although these pulses are smoothed by the overlap of spawners who have entered the stream on different days, spikes in counts are still quite visible in lots of stream data. This kind of variation (caused by the variability in entry process) is not counted in the spawning abundance model explicitly but treated as observation error. Excessive "observation" error in combination with few postpeak counts can cause convergence problems for the Gibbs sampler.

In our example, we were unable to differentiate variability in the mean date of escapement (τ_m^2) from variability in the duration of escapement (τ_s^2). By retreating to the simpler M_y-S or M-S_y model, we were able to complete the analysis. Refined stream entry models that used environmental conditions, such as floods, rainfall, might explain some of the higher frequency variation in spawner counts and thus increase the estimability of the timing parameters of the HBM.

As Millar and Meyer (2000) point out, "Fitting a model is just the beginning". In this paper, we addressed the important problem of model selection and adequacy using predictive model determination techniques. Such validation steps are rare in fisheries applications of Bayesian methods, probably due to the computational burden. Bayesian methods require a lot of effort just for model fitting; sometimes model assessment and selection are not well addressed (Millar and Meyer 2000). The Gibbs sampler and other MCMC techniques enable users to tackle complex models that is impossible to cope with by other methods. The predictive model determination quantities that we used in this example can be easily calculated in the Gibbs sampling process; so routine model checking should not be too onerous.

An additional method of borrowing strength would be to incorporate spatial relationships as another hierarchical level in the model. In Southeast Alaska, pink salmon in neighboring streams often have similar run timing. They also experience correlated fluctuations in escapement, in response to both a common environment and to a common harvest regime. Incorporating these common patterns would reduce the uncertainty in escapement estimates even further. Weir studies on representative index streams would further increase the benefit of this approach.

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Appendix A. The Metropolis steps

We use a Metropolis step with a normal proposal distribution $N(\vartheta_i^* \mid \vartheta_i^{(t-1)}, SD_i^2)$, $i = 1, \ldots, p$, to update each of those parameters with no standard-form full conditional distributions, where $\vartheta_i^{(t-1)}$ is the current value of a parameter, the ϑ_i^* is a candidate value, and SD_i is a specified standard deviation for the proposal distribution. In a Metropolis step, the ϑ_i^* is accepted as an update with probability

$$\min\left(1, p(\vartheta_i^* \mid \{\vartheta\}_{j \neq i}) / p(\vartheta_i^{(t-1)} \mid \{\vartheta\}_{j \neq i})\right)$$

otherwise, it is rejected and we set $\vartheta_i^{(t)} = \vartheta_i^{(t-1)}$.

The choice of SD_i affects the efficiency of Metropolis steps and thus the whole algorithm. High values of SD_i result in large proposal moves and low acceptance rate because most of the candidate moves may step into low-density area of the posterior distribution and thus be rejected. Small values of SD_i result in high acceptance rate and slow movement of the chain.

The performance of the Metropolis algorithm can be expressed by the acceptance rate of the candidate draws in the Metropolis steps. Theoretical and empirical results show that the acceptance rate in the range 20% ~ 50% (depending on number of parameters) provides optimal performance (Gelman et al. 1995). For multilevel models, Browne and Draper (2000) proposed an acceptance rate of 40% ~ 60% for univariate updating.

To increase the efficiency of the Metropolis algorithm, we adopt an adaptive tuning step similar to that of Browne and Draper (2000) to tune the SD_i before generating sample draws for inference. The goal of the tuning is to obtain a target acceptance rate around 50%. The adaptive step is stopped after a fixed number of iterations, after which the burn-in period (the preconvergence period) and main monitoring run (the postconvergence period) is started.

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Appendix B. MCMC convergence diagnostics

A critical issue in using MCMC methods is how to determine when random draws have converged to the posterior distribution (Gelman et al. 1995). Best et al. (1995) have developed a collection of S-plus routines called CODA for convergence diagnostics of MCMC sampling. Several general diagnostic methods have been incorporated in this free package, including methods proposed by Heidelberger and Welch (1983), Geweke (1992), Gelman and Rubin (1992), and Raftery and Lewis (1992). CODA also provides summary estimates, kernel density plots, autocorrelations and cross-correlations for the monitored quantities. We used the results from these CODA routines to assess convergence of our MCMC chains. We provide a summary of their underlining theoretical considerations, implementation and criteria for assessing convergence in Table B1.

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Table B1 A summary of MCMC convergence diagnostics.

Aspect monitored	Diagnostic	#Chains	Diagnostic steps	Theory and convergence criterion
Trend	Geweke (1992)	Single	1. Compare the mean in the first x% (e.g. 10%) portion of the simulation output of a quantity of interest with that containing the last y% (e.g. 50%) of the output by a Z-score. 2. If $\|Z\|$ is extreme, the first x% can be discarded and the Geweke's diagnostic be repeated and so on.	If the chain is in stationary, the means of the values early and late in the sequence should be similar. The diagnostic is a Z-score that is the difference of the two means divided by an asymptotic standard error of the difference of the means. As length of chain $\rightarrow \infty$, $Z \rightarrow N(0, 1)$, so Geweke $\|Z\| < 2$ means convergence
	Heidelberger and Welch's (1983)	Single	1. Conduct a test for the null hypothesis of stationarity for the *entire simulation output of a quantity first.* 2. If the null hypothesis is rejected, the test is repeated after discarding the first, e.g., 10% of the series. This process will continue until either the null hypothesis is passed or 50% of the iterations have been discarded and the null hypothesis is still rejected. In the latter case, CODA will report the failure of the stationarity test and the value of C-$vonM$ statistic. 3. For the portion of the chain passing the stationarity test, a half width (1.96 × asymptotic standard error) test is further conducted to check if the half width < posterior mean × ε (a small fraction, e.g. 0.1). If this test is rejected, a longer run is needed to increase the accuracy of the estimates.	Use a Brownian bridge theory and the Cramer-von Mises statistic (C-$vonM$) for the stationarity test. The 95th percentile of C-$vonM$ is 0.46, which can be used to judge if the stationary test is passed

Table B1 (*continued*).

Autocorrelation	Raftery and Lewis (1992)	Single	1. Suppose we wish to estimate the 2.5th percentile to within ± 0.5 with probability 0.95 for each parameter. 2. First take a pilot run of at least N_{min} iterates (the minimum number of iterations needed to obtain the desired accuracy of the estimate if the draws were independent). This diagnostic provides recommendations for an initial number of iterates to discard M (burn-in), a total number of iterates N needed to obtain the desired accuracy of the estimate for which every kth is stored, and finally a "dependence factor" $I = N/ N_{min}$.	The value of I measures the increase in number of iterations needed to reach convergence due to dependence between the samples in the chain. Values of I near 1.0 indicate good mixing, whereas values of I much greater than 1.0 indicate high autocorrelation within the chain (Raftery and Lewis (1992) suggest that $I > 5.0$ indicates problems).
Mixing of sequences	Gelman and Rubin's (1992)	Multiple	• Run multiple chains with overdispersed starting points to see if all the chains can converge to a same stationary distribution. CODA reports the median and the 97.5 percentile (estimated from the second half of each chain) of the sampling distribution for a shrink factor. Values of these two quantiles near 1.0 may mean effective convergence of all the chains.	Estimates a "shrink factor" that involves both the between- and within-chain variances. The shrink factor approaches 1.0 when the chains have mixed; at this point, the two variance components are essentially equal (Gelman et al. 1995).

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Appendix C. Model checking and comparison

In this appendix we will address the important problem of model comparison and adequacy checking. Any model is necessarily a simplification of complex real-world phenomena. Hence, checking the fit of a model to data and other knowledge is always important. Nevertheless, such validation steps are rare in fisheries applications of Bayesian methods, probably due to the computational burden (Millar and Meyer 2000). We apply various predictive model evaluation techniques (Gelfand 1996) for model adequacy checking and comparison in a HBM setting. These model determination quantities can be easily calculated during the Gibbs sampling processes, therefore routine model checking should not be too onerous.

Cross-validation residuals

Standardized cross-validation (cv) residuals are defined as

$$\text{(C1)} \qquad r_{y,t}^{cv} = \frac{c_{y,t} - E(c_{y,t} \mid D_{(y,t)})}{\sqrt{\operatorname{var}(c_{y,t} \mid D_{(y,t)})}}$$

where $c_{y,t}$ denotes the observed count and $D_{(y,t)}$ denotes all elements of the observed data set $D = \{c_{y,t}\}$ except $c_{y,t}$. The quantities $E(c_{y,t} \mid D_{(y,t)})$ and $\mathrm{var}(c_{y,t} \mid D_{(y,t)})$ are the expected value and the variance of $c_{y,t}$ from the cross-validation predictive distribution $p(c_{y,t} \mid D_{(y,t)})$. Once we have obtained a sample $\{\varphi_k^*\}$, where φ is the parameter vector and $k = 1,..,G$, from the posterior $p(\varphi \mid D)$ through MCMC or other sampling techniques, $E(c_{y,t} \mid D_{(y,t)})$ can be calculated using the following approximation for a large data set (Carlin and Louis 1996, p. 219):

$$\text{(C2)} \quad E(c_{y,t} \mid D_{(y,t)}) \approx \frac{1}{G}\sum_{k=1}^{G} E(c_{y,t} \mid \varphi_k^*)$$

where $E(c_{y,t} \mid \varphi_k^*) = \eta_{y,t}(\varphi_k^*)$. The variance term can be calculated using

$$\text{(C3)} \quad \mathrm{var}(c_{y,t} \mid D_{(y,t)}) = E(c_{y,t}^2 \mid D_{(y,t)}) - [E(c_{y,t} \mid D_{(y,t)})]^2$$

and

$$\text{(C4)} \quad E(c_{y,t}^2 \mid D_{(y,t)}) \approx \frac{1}{G}\sum_{k=1}^{G}\left[\mathrm{var}(c_{y,t} \mid \varphi_k^*) + [E(c_{y,t} \mid \varphi_k^*)]^2\right]$$

Here $\mathrm{var}(c_{y,t} \mid \varphi_k^*)$ is simply the variance of the counts, or σ^2.

We used the skewness and kurtosis of the standardized residuals to assess the normality of the residuals. Other diagnostic analyses traditionally performed on residuals can also be used.

Conditional predictive ordinate

We compute the conditional predictive ordinate (CPO), which is the actual value of the cross-validation predictive distribution $p(c_{y,t} \mid D_{(y,t)})$, for comparison of alternative model forms. The Monte Carlo estimate of the CPO (Gelfand 1996) is given by

$$\text{(C5)} \quad \text{cpo}_{y,t} = G\left(\sum_{k=1}^{G}(1/f(c_{y,t} \mid \varphi_k^{*}))\right)^{-1}$$

where

$$f(c_{y,t} \mid \varphi_k^{*}) = (1/\sqrt{2\pi\sigma^2})\exp(-(c_{y,t} - (\eta_{y,t})_k^{*})^2/2\sigma^2)$$

is the likelihood evaluated at φ_k^{*}. The negative cross-validation log-likelihood (ncvLogL = $-\sum \log(\text{cpo}_{y,t})$) (Spiegelhalter et al. 1997) is used to compare alternative models, with a smaller value of ncvLogL indicating the preferred model.

Deviance information criterion (DIC)

We also use DIC (Spiegelhalter et al. 1998) for our model comparisons. Let the deviance $D(\theta)$ be minus twice the log-likelihood of the data and the θ as the parameter vector. Then

DIC = “fit” + “complexity”,

where “fit” is defined as the posterior mean of $D(\theta)$, $\overline{D} = E(D)$, and “complexity” is represented by the effective number of parameters p_D, defined as $p_D = \overline{D} - D(\theta)$, where

$D(\bar{\theta})$ is the deviance evaluated at the posterior expectations $\bar{\theta}$. A smaller value of DIC indicates a better fitting model.

DIC can be readily calculated during an MCMC run by monitoring both θ and $D(\theta)$. At the *k*th iteration of MCMC run, we define

$$\text{(C6)} \quad D(\theta_k^*) = -2\ln(f(c_{y,t} \mid \theta_k^*)) = \sum_{\{y,t\}} \left(\ln(2\pi\sigma^2) + (c_{y,t} - (\eta_{y,t})_k^*)^2 / \sigma^2\right)$$

DIC is very useful for comparing hierarchical models, where the number of parameters is not clearly defined. With non-hierarchical models, p_D is asymptotically the true number of parameters and DIC is thus equivalent to the more familiar Akaike Information Criterion (AIC).

Appendix C references

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Chapter 2. A comparison of salmon escapement estimates using a hierarchical Bayesian approach versus separate maximum likelihood estimation of each year's return[2]

Abstract

In this simulation study, we compared the performance of a hierarchical Bayesian approach for estimating salmon escapement from count data to that of separate maximum likelihood estimation of each year's escapement. We simulated several contrasting counting schedules resulting in data sets that differed in information content. In particular, we were interested in the ability of the Bayesian approach to estimate escapement and timing in years where few or no counts are made after the peak of escapement. We found that the Bayesian hierarchical approach was much better able to estimate escapement and escapement timing in these situations. Separate estimates for such years could be wildly inaccurate. However, even a single postpeak count could dramatically improve the estimability of escapement parameters.

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[2] An earlier version of this chapter is published as Adkison, Milo D., and Su, Zhenming. 2001. A comparison of salmon escapement estimates using a hierarchical Bayesian approach versus separate maximum likelihood estimation of each year's return. Can. J. Fish. Aquat. Sci. 58: 1663-1671.

Introduction

Estimates of escapement in many salmon stocks are calculated based on aerial or foot counts. Most often, the magnitude of escapement is estimated using an ad hoc "area-under-the-curve" (AUC) methodology (Neilson and Geen 1981; Perrin and Irvine 1990; English et al. 1992). Recently, likelihood-based methods have been developed that offer the advantage of a statistical framework (Quinn and Gates 1997; Hilborn et al. 1999), allowing the user to calculate the uncertainty of such estimates. Additionally, these models estimate parameters defining the timing of the escapement, useful in run reconstruction techniques (Starr and Hilborn 1988; Mundy et al. 1993; Templin et al. 1996; Chapter 3).

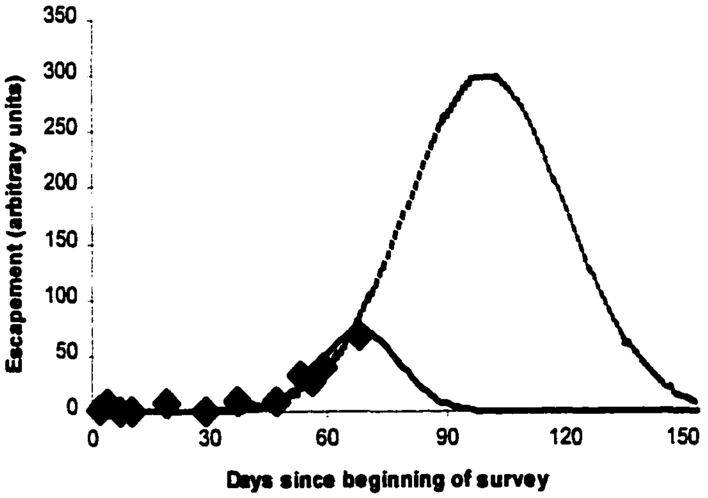

Fig. 2.1 Two plausible model fits to a hypothetical set of escapement counts with no postpeak information. The solid line illustrates a fit to the data that implies a smaller escapement with an earlier timing than the fit illustrated by the dashed line.

Likelihood-based methods have difficulties with certain types of count data (Hilborn et al. 1999). Counts may be sparse, and in particular may cease after escapement goals have been met. This can cause positive bias in estimating the magnitude of the escapement, timing, and spread in timing (Fig. 2.1). Hilborn et al. (1999) give an example (1990 counts of pink salmon (*Oncorhynchus gorbuscha*) in Herring Creek of Prince William Sound, Alaska) where the last count was the highest. This led to very high escapement estimates, because a continued increase in abundance to a late peak could not be discounted. An AUC approach has similar problems with such data. Usually it is assumed that escapement declines linearly to zero over a period of one half the stream life; this may result in a large error when the biological reality differs (Hilborn et al. 1999).

An examination of more complete data from years where counts were continued longer suggested late runs were implausible. Adding this historical information as a component of the likelihood (a pseudo-Bayesian approach) constrained the results to biologically plausible scenarios.

A natural way to incorporate "prior" information about run timing from years where count data span the peak of escapement to aid estimation in years without postpeak counts is to use a hierarchical model. In Chapter 1, we developed a hierarchical Bayesian model (HBM) and an estimation methodology that explicitly accounts for the similarity in run timing among years and applied it to estimating historical pink salmon escapement in a Southeast Alaska stream. In this paper we use simulation to compare the theoretical performance of our hierarchical Bayesian approach to non-hierarchical likelihood-based methods for escapement estimation.

Methods

A salmon spawning abundance model

In our model (details in Chapter 1), the number of salmon in the stream on a particular day (η_t) can be expressed as follows:

(2.1) $\eta_t = E\Phi_t$

where Φ_t is the proportion of the total escapement (E) in the stream on day t. Φ_t is the result of two processes. The first is entry of fish into the stream, which we model as proportional to a normal distribution with a mean date of M and a standard deviation in entry date of S. The second is the loss of some of the fish that are in the stream due to natural mortality. We assume each fish entering the stream on a given date has an identical lifespan. This stream life is known to decline with the date of entry (Neilson and Geen 1981; Dangel and Jones 1988; Fukushima and Smoker 1997). We use an exponential decay equation to express stream life (λ_t) by date of entry t:

(2.2) $\lambda(t) = \phi_1 e^{-\phi_2(t-M)}$

where ϕ_1 and ϕ_2 are two shape parameters estimated separately from independent stream life surveys and M is the mean date of arrival.

Let c_t denote the observed stream count in day t. Following Quinn and Gates (1997), we assume a normally distributed measurement error in the square root of the count:

(2.3) $\sqrt{c_t} = \sqrt{\eta_t} + \varepsilon_t$

with $\varepsilon_t \sim N(0,\sigma^2)$, where σ^2 is the data error variance.

There are thus four unknown parameters for each year in this model: M, S, E and σ^2.

Separate estimation for each year

Given particular values of M, S, and E, the model equations above can be used to predict the number of fish in the stream on any date (η_t). Maximum likelihood parameter estimates (MLEs) for a particular year can thus be estimated using a nonlinear search algorithm that selects candidate values of M, S, and E to minimize SSQ, where SSQ is the following:

$$(2.4) \qquad SSQ = \sum_t \left(\sqrt{c_t} - \sqrt{\eta_t(M,S,E)}\right)^2$$

The bias-corrected estimate of σ^2 is obtained by dividing SSQ by the number of counts minus the number of parameters.

Confidence intervals for each parameter were calculated using a bootstrap approach (Manley 1997). A profile likelihood method (Hilborn and Mangel 1997) yielded similar results (not shown). In each bootstrap trial, residuals from the MLE fit (the differences between the square root of the counts and the square root of the predicted counts) were randomly sampled with replacement and added to the MLE predictions to create a pseudo-data set. Parameter estimates for each pseudo-data set were then calculated. This bootstrap was then repeated 1 500 times. These bootstrap estimates were ordered by size, and then the 15th and 85th percentiles were taken as the lower and upper bounds of the confidence interval.

Bayesian estimation of all years simultaneously

If the behavior of the fish can be assumed to be similar in some respects from year to year (Heard 1991), simultaneously estimating the parameters of all years of data should result in more powerful inference. A hierarchical structure can be imposed on this model by assuming that the mean date of arrival and the logarithm of the standard deviation of arrival date are random samples drawn from normal probability distributions. Thus:

(2.5) $M_y \sim N(\mu_m, \tau_m^2)$

(2.6) $\ln(S_y) \sim N(\mu_s, \tau_s^2)$

This model is termed the M_y-S_y model. One variant that assumes that S is constant from year to year, the M_y-S model, and another that assumes M is constant, the M-S_y model, were used for a few trials.

A Bayesian framework for generating estimates from this hierarchical model is detailed in Chapter 1. After specifying vague priors for the hyperparameters μ_m, τ_m^2, μ_s, τ_s^2, the sampling error in the counts (σ, assumed constant for all years), and the annual escapements $\{E_y\}$, we are able to make inferences about all parameters.

Point estimates and credible intervals for each parameter are obtained by drawing samples from the posterior distribution. A Metropolis-Gibbs sampling methodology (details in Chapter 1) is used to generate random draws. An initial adaptive step of 3000 iterations is used to tune the variance of the proposal distribution, in order to obtain an acceptance rate of 50% for the Metropolis steps (Chapter 1). Then the sampler is run to generate another 15 000 random draws, of which the last 13 000 are kept. For each parameter, the median of the 13 000 values is used as an indicator of central tendency and the 15th and 85th percentiles as an indicator of uncertainty.

Simulation studies

We generated 20 years of simulated stream count data with properties similar to those of Kadashan Creek, Alaska (Chapter 1). We used a normal distribution with $\mu_m =$ 210 and $\tau_m^2 = 25$ to generate the peak date of escapement (M_y) and a normal distribution with $\mu_s = 2.5$ and $\tau_s^2 = 0.07$ to generate $\ln(S_y)$, the spread in dates of escapement. The total escapement in each year (E_y) was generated from a uniform distribution with end bounds of 10^4 and 10^6. The simulation was then conducted as follows:

(1) Generate true values of yearly parameters: $M_y^{true}, \ln(S_y^{true})$ and E_y^{true}, $y = 1$ to 20.

(2) Calculate true spawner abundance by date for each year, $\{\eta_{y,t}\}$, $t = 1, 2, \ldots, n_y$ using the parameter values generated in step 1.

(3) Generate a survey scheme for each year as follows. Assume that the surveys are conducted each year from day 170 (June 18) to 250 (Sept. 6) at intervals of two to ten days (Chapter 1). Use a uniform distribution to generate the intervals between the surveys.

(4) Produce simulated counts using $\sqrt{c_{y,t}} = \sqrt{\eta_{y,t}} + e_{y,t}$, where $e_{y,t} \sim N(0, 2200)$ (approximately the error variance estimated using the M_y-S_y model with Kadashan Creek SQRT transformed data (Chapter 1)). Negative values occasionally generated by the right side of the above equation (about 8% of simulated values, mainly the smaller counts) are set to zero.

(5) HBM estimation: Using count data from all 20 years, draw samples from the posterior distribution of the parameters by running the Gibbs sampler (see the previous section). Then calculate the median, 15th and 85th percentiles of the posterior distribution of each parameter estimate. Record whether the interval between the 15th and 85th percentile contained the true parameter value.

(6) Separate maximum likelihood estimation: Generate estimates of the annual parameters for each year using only that year's counts. Calculate the MLE of each parameter, and then construct a bootstrap 70% confidence interval. Record whether the interval contained the true parameter value. To prevent extremely long searches for poorly defined MLE's, the parameter estimation was judged to have failed if the search algorithm failed to converge. This was indicated functionally when the search algorithm continued exploring values of M_y of greater than 300. Parameter estimates from these failures were not included in calculating RB or CV values below.

(7) For each estimation method, calculate the relative bias (RB) of each parameter as the percent deviation of its posterior median (or median from the bootstrap of

MLE) from its true value: 100 × (median – true)/true. Also calculate a coefficient of variation-like quantity (CV) using: (85th percentile –15th percentile)/(2 × median) or (width of 70% confidence interval)/(2 × median) to quantify the precision of the parameter estimates. These two quantities are robust to outliers.

(8) Repeat 7 steps100 times.

We summarized the RBs and CVs of each parameter across these 100 simulated data sets (2000 years in total) using their medians, 15th, and 85th percentiles. We calculated coverage probabilities for confidence intervals from separate estimation and for credible intervals from Bayesian estimation.

Scenarios run

We considered six simulation scenarios (Table 2.1); all except the first differed primarily in the number and timing of counts taken after the peak in escapement. Scenario D_0 examined the performance of estimation absent errors in counting; instead of using the counts (c_y) we used the actual numbers of fish in the stream on those dates (η_y).

Scenario *All* used all the counts from throughout the spawning season. Scenario *P1WK*, *P2WK*, and *P4WK* contained only one count taken after the peak in escapement. In scenario *P1WK*, this count was the first taken after the peak, on average one week later. This scenario was similar to much of the data seen in Southeast Alaska pink salmon counts. In scenario *P2WK* this count was taken approximately two weeks postpeak in the midst of the decline, and in scenario *P4WK* the count was taken around four weeks postpeak, when few spawners remained. By comparing scenario *All* to scenarios *P1WK*, *P2WK*, *P4WK*, and the first five years only of scenario *5-15* (referred to below as *1st 5*), we were able to determine the importance of postpeak count data, and the relative importance of particular postpeak counts.

Finally, in scenario *5-15* we did not use any postpeak counts from the first five years of each trial but did use counts throughout the spawning season for the other 15 years; this scenario tested the ability of the Bayesian approach to use timing information from the last 15 years to salvage escapement estimates for the first five years. In presentations of the results of separate estimation, we lump the outcomes from these last 15 years with those of scenario *All*.

Table 2.1 Simulation scenarios

Scenario	Description
D_0	Escapement observed without error
All	All count data included
P1WK	Only one count made after the date of peak escapement, about 1 week later
P2WK	Only one count made after the date of peak escapement, about 2 weeks later
P4WK	Only one count made after the date of peak escapement, about 4 weeks later
5-15	The first 5 years with no counts after the peak escapement, other 15 years with complete data

Results

Importance of observation error

In the absence of observation error, both separate estimation and hierarchical Bayesian methods perfectly estimated the annual parameters M, S, and E (RB = 0%, CV = 0%). However, it was still not possible to perfectly estimate the values of the hyperparameters in the HBM (Table 2.2). This is because the 20 years of data were essentially a finite random sample of size 20 from the hyperprior distribution. For example, the expected CV of estimating the mean μ_m from 20 random values of M_y generated according to the distribution $M_y \sim N(210, 25)$ is $\sqrt{V/n}/\mu = \sqrt{25/20}/210 =$ 0.53%. In our simulations the median CV of our Bayesian estimate of μ_m under scenario D_0 was 0.6%, roughly the value expected (Table 2.2). When counting errors were introduced, annual parameters were also no longer perfectly estimated (see below).

Table 2.2 Median values of RB and CV for the hyperparameters obtained from 100 simulated data sets for the M_y-S_y model under six scenarios.

	RB (%)						CV (%)					
	D_0	All	P1WK	5-15	P2WK	P4WK	D_0	All	P1WK	5-15	P2WK	P4WK
μ_m	-0.02	0.16	0.51	0.49	0.24	0.48	0.6	0.6	0.7	0.6	0.6	0.6
τ_m^2	1.11	-3.71	-5.91	-2.78	-0.85	0.59	35.8	37.9	48.3	43.4	41.5	43.5
μ_s	-0.91	0.89	1.26	1.65	0.17	0.33	2.5	2.7	3.0	2.7	2.9	2.6
τ_s^2	-3.54	5.92	1.34	-5.74	6.64	-11.74	35.5	41.2	52.2	43.2	46.4	48.7

Ability of Bayesian methods to salvage years with no postpeak counts

Both separate estimation and HBM methods produced fairly good estimates of *M*, ln(*S*), and SQRT(*E*) when postpeak data were available (e.g., scenario *All*, Fig. 2.2-2.3). Estimates of escapement timing (*M*, ln(*S*)) and especially of escapement abundance (SQRT(*E*)) from years with no postpeak counts were considerably poorer (scenario *1st 5*, Figs. 2.2-2.3). In part, the apparent relative precision of estimates of *M* is an artifact of the arbitrary scale of measurement; by assigning a value of 210 to the calendar date of the midpoint of the run, the RB and CV of *M* are naturally smaller than those for ln(*S*), whose mean is only 2.5.

With no postpeak data, both estimation methods showed positive biases (scenario *1st 5*, Fig. 2.2). The median RB was only slightly displaced from zero, but the distribution was skewed upwards. Without postpeak data, separate estimation failed to converge to reasonable parameter estimates ($M > 300$) almost 1/3 of the time (Table 2.3). Each of these trials would have resulted in a large RB. For example, for *M* in each "failed" trial we would have had an RB greater than 100% × (300-210)/210 = 43%. Fig. 2.2 thus underestimates the positive bias from using separate estimation because these frequent estimation "failures", which would have resulted in extremely large values of RB (and CV), are not included. In a separate 500 trials where we did not stop the search

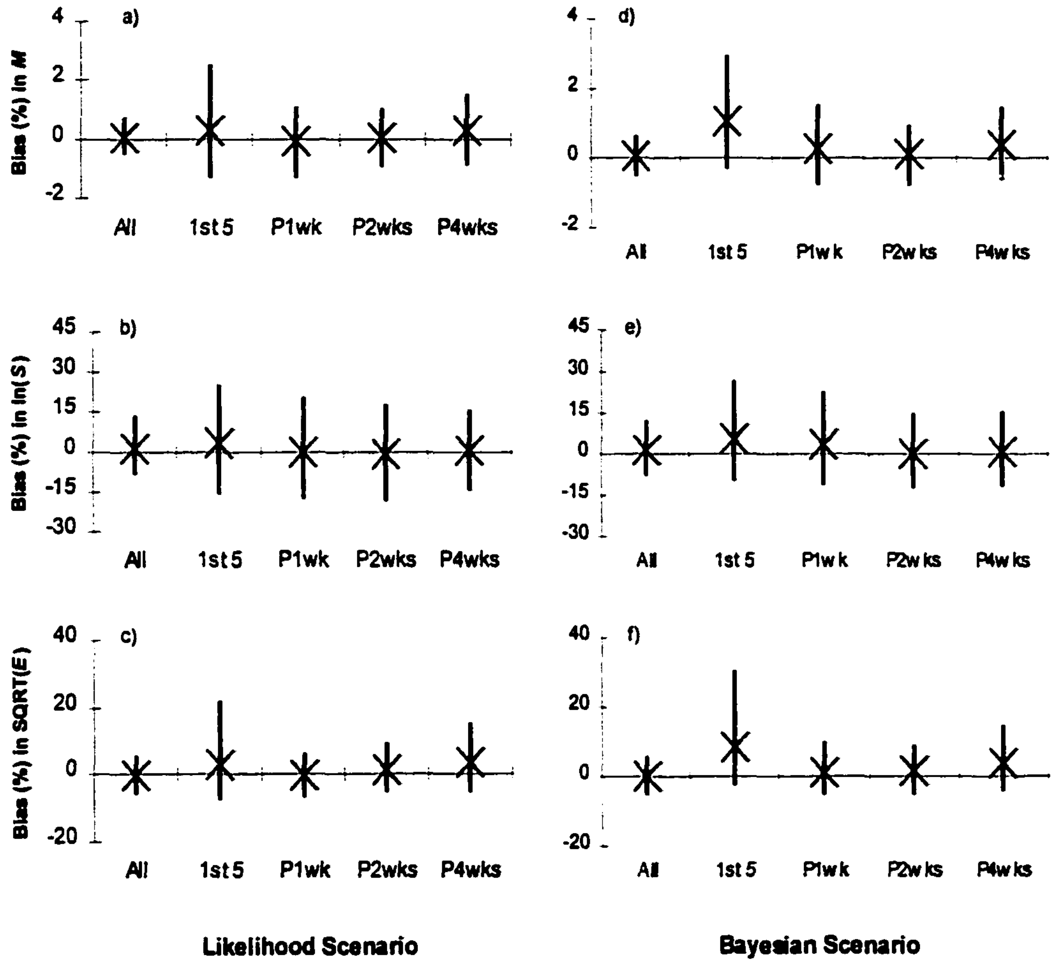

Fig. 2.2 RB of annual escapement timing and abundance parameters *M*, ln(*S*) and SQRT(*E*) for various scenarios.

The ends of the vertical line are the 85th and 15th percentiles of the RB; the cross indicates the median RB. Results are shown for both (*a-c*) separate maximum likelihood estimation and (*d-f*) the M_y-S_y HBM. The label *1st 5* indicates the results from the first 5 years of scenario *5-15*; label *All* includes the results from scenario *All* plus the last 15 years of scenario *5-15*.

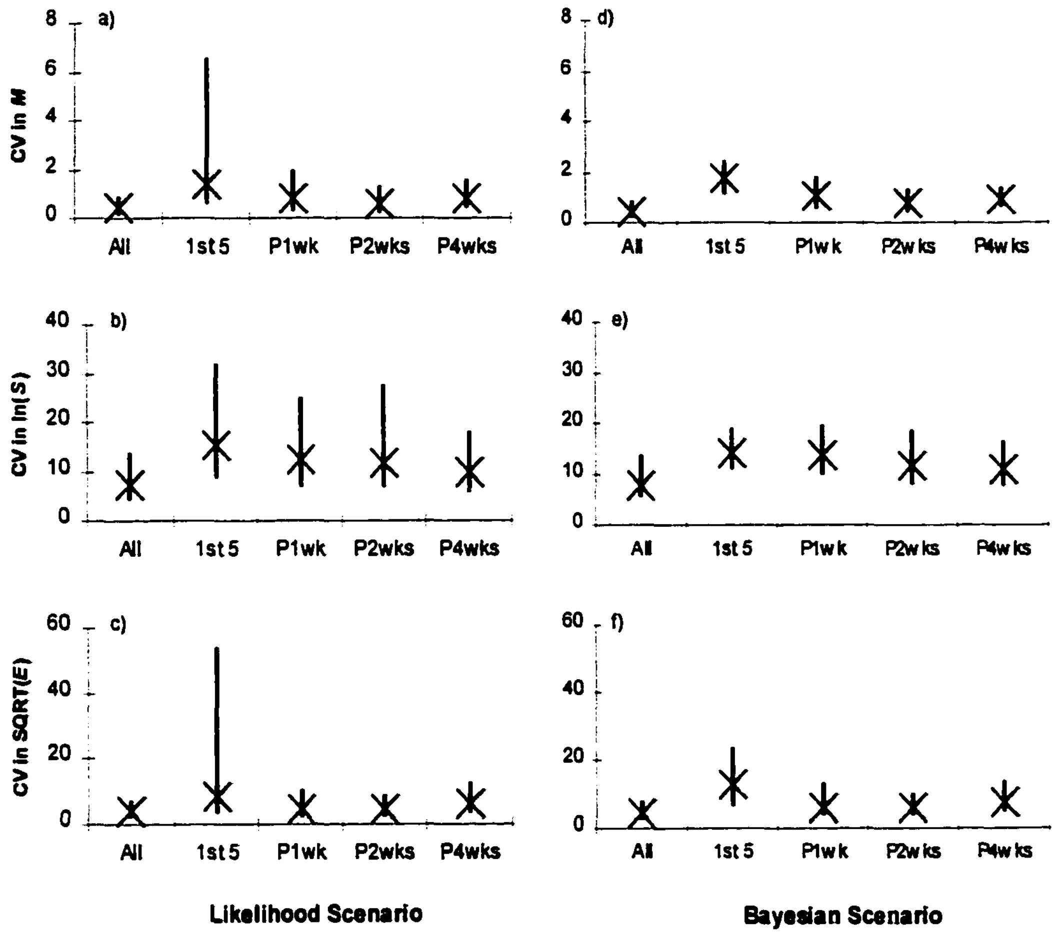

Fig. 2.3 CV of annual escapement timing and abundance parameters *M*, ln(*S*) and SQRT(*E*) for various scenarios.

The ends of the vertical line are the 85th and 15th percentiles of the RB; the cross indicates the median RB. Results are shown for both (*a*-*c*) separate maximum likelihood estimation and (*d*-*f*) the M_y-S_y HBM. The label *1st 5* indicates the results from the first 5 years of scenario *5-15*; label *All* includes the results from scenario *All* plus the last 15 years of scenario *5-15*.

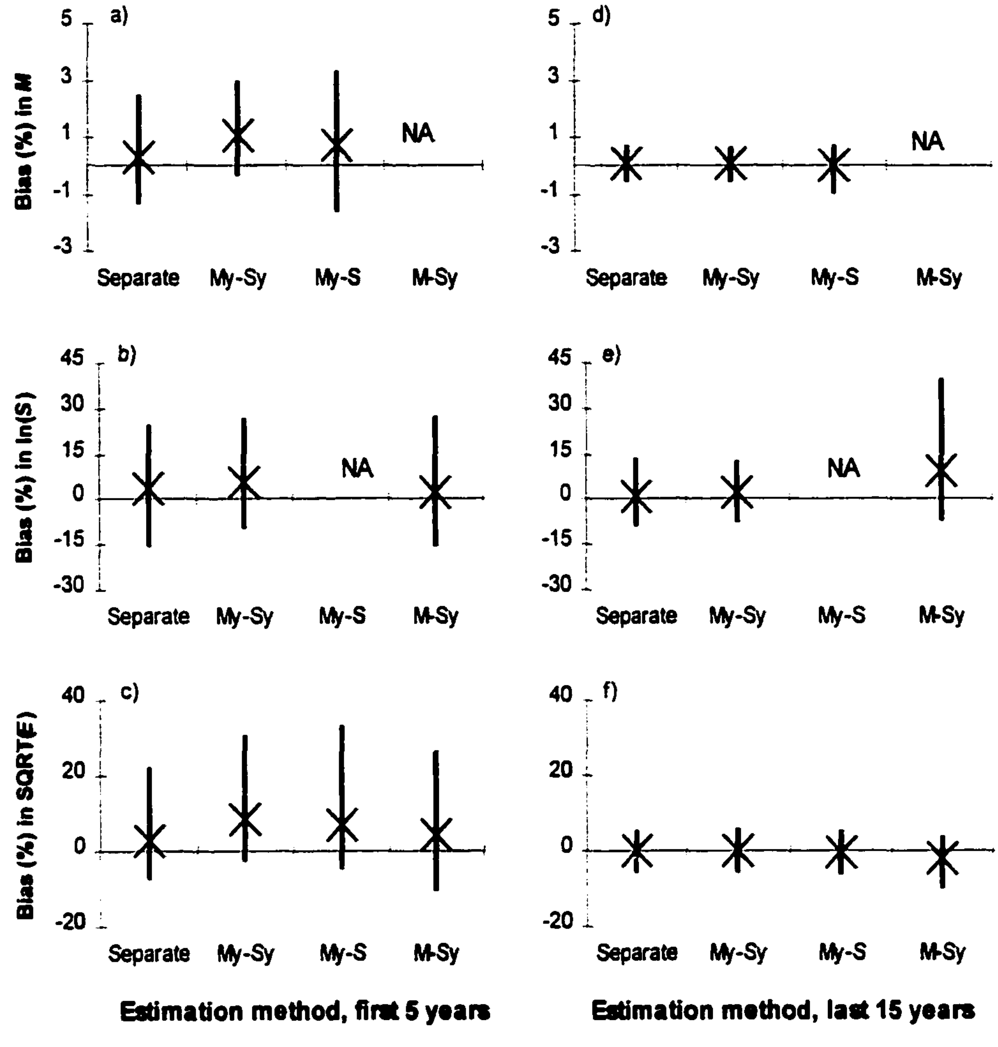

Fig. 2.4 RB of annual escapement timing and abundance parameters *M*, ln(*S*) and SQRT(*E*) for (*a-c*) the first 5 years and (*d-f*) the last 15 years of scenario *5-15*.

The ends of the vertical line are the 85th and 15th percentiles of the RB; the cross indicates the median RB. Results are shown for both separate maximum likelihood estimation and three HBMs. NA, not applicable.

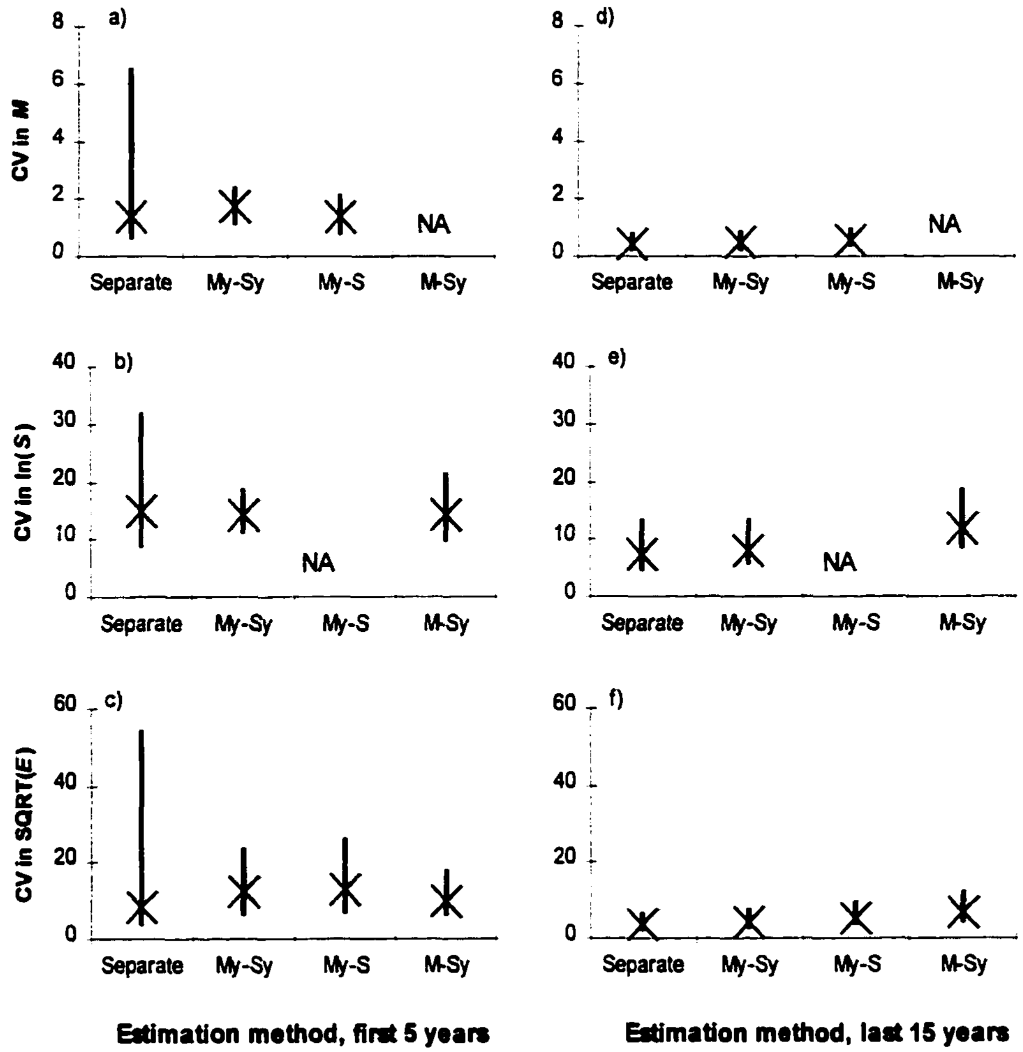

Fig. 2.5 CV of annual escapement timing and abundance parameters *M*, ln(*S*) and SQRT(*E*) for (*a*-*c*) the first 5 years and (*d*-*f*) the last 15 years of scenario *5-15*.

The ends of the vertical line are the 85th and 15th percentile of the CV; the cross indicates the median width of the CV. Results are shown for both separate maximum likelihood estimation and three HBMs. NA, not applicable.

for parameter estimates when the estimate of *M* exceeded 300, the 85th percentile of RB increased to 27%, 32%, and 303% for *M*, ln(*S*), and SQRT(*E*), respectively.

Bayesian estimates also were positively biased when postpeak data were absent. Nonetheless, the HBM approach still outperformed separate estimation when postpeak data were lacking (compare the width of the CV intervals for scenario *1st 5* in Fig. 2.3; although the median RB and CV appear larger for the HBM, this is an artifact of deleting trials where separate estimation completely failed).

Differences between the performance of M_y-S_y, M_y-S, and M-S_y Bayesian models were relatively minor compared to the differences between the HBMs and separate estimation (Table 2.3, Figs. 2.4-2.5), particularly in the CV of estimates for the first 5 years of scenario *5-15* (Fig. 2.5*a-c*). Again, for separate estimation the 85th percentile of RB and CV for the first five years of scenario *5-15* is underestimated due to excluding the "failures". Performance of Bayesian estimates for the last 15 years of scenario *5-15* were comparable to those from scenario *All*, indicating that estimates in years when postpeak counts are available are not much affected by the uncertainty in years when they are not.

The importance of particular postpeak counts

Any postpeak data resulted in greatly improved estimates compared to those obtained when postpeak counts were lacking (Figs. 2.2-2.3). A single count taken 1, 2, or 4 weeks after the peak of escapement appeared to contain almost as much information about the magnitude and timing of escapement as all postpeak counts. The estimated duration of the run (ln(*S*)) benefited the least from the addition of a single count taken after the peak (Fig. 2.2*b*, 2*e*, 3*b*, 3*e*); using the HBM approach was less likely to result in large CVs (Fig. 2.3*e*).

There were mostly minor differences in information content among the various postpeak counts. A count taken one week postpeak was least informative, possibly because the magnitude of the counting error was comparable to the expected decline in in-stream abundance, confusing interpretations. With separate estimation, a 6.6% failure rate was seen in scenario *P1wk* (Table 2.3). These were probably instances where the counting error from the post peak count resulted in an overestimate, with the result that the series of counts did not show a peak.

Table 2.3 Percent of trials in which separate estimation 'failed', i.e., the maximum likelihood estimate of the mean date *M* was greater than day 300.

Trial	Failure %
All + last 15 years of 5-15	0.0
Last 5 years of 5-15	32.8
P1WK	6.6
P2WK	0.3
P4WK	0.0

Coverage properties of intervals

The coverage of 70% confidence intervals from separate estimation was poor, less that 60% when postpeak counts were available and even lower when postpeak data were absent (Table 2.4). The coverage of 70% Bayesian credible intervals was only slightly below 70% for most trials. One exception was the first five years of scenario *5-15*, where the actual coverage for all three parameters was less than 65% (Table 2.4). Nonetheless, this coverage was better than that of separate estimation. Thus, bootstrap uncertainty intervals from separate estimation may underestimate the true uncertainty, while the HBM provides nearly unbiased estimates of the uncertainty intervals.

Discussion

Our hierarchical Bayesian methods can salvage escapement estimates from years lacking postpeak counts if the assumptions are met, particularly the assumption that the variation in the timing of escapement is adequately represented by the set of years for which postpeak counts exist. This assumption is biologically credible, although climatic shifts or shifts in the relative contribution of constituent substocks could affect the timing of escapement. More likely are anthropogenic perturbations of escapement timing: e.g., changes in the timing of harvests or genetic contamination of the stock.

Table 2.4 Actual coverage (%) of 70% confidence intervals from separate estimation and 70% credible intervals from Bayesian estimation.

Estimation	Scenario	*M*	*S*	*E*
Bayesian	ALL + last 15 of 5-15	65	70	65
	First 5 of 5-15	61	64	59
	P1WK	65	65	70
	P2WK	65	68	70
	P4WK	65	65	65
Separate	ALL + last 15 of 5-15	57	58	59
	First 5 of 5-15	55	55	50
	P1WK	57	56	54
	P2WK	55	54	53
	P4WK	57	57	54

Estimates of escapement abundance and timing based solely on the count data for that year may yield unreasonable results if postpeak data are lacking. Unfortunately, such data sets may be common as managers are tempted to discontinue expensive stream counts when escapement goals have been met. Just as in a linear regression, where much of the information about the slope is contained in the data with the largest and smallest x-values (Draper and Smith 1981), not all postpeak counts are of equal value. Counts immediately after the peak contain the least information. A decreased count right after the peak may plausibly be interpreted as due to sampling error, with escapement possibly still increasing. Since larger escapements with later run timing are still plausible, estimates of *M*, *S*, and *E* are all upwardly biased. Nonetheless, any postpeak data appear to be highly valuable. Operationally, a manager will not be able to predict the date of the peak exactly. To ensure at least one postpeak count, it would be better to conduct the final count later rather than too early.

In our model we assume our count data are unbiased estimates of the number of fish in the watershed. In reality, count data are usually biased downwards and may have other biases as well (Dangel and Jones 1988; Bue et al. 1998; Jones et al. 1998). Any biases are necessarily propagated through the analysis and affect our estimates of escapement. Hilborn et al. (1999) dealt with this problem by explicitly modeling the bias, incorporating variability in observer efficiency based on a comparison of aerial counts to weir counts in a representative stream. Admitting uncertainty about observer efficiency greatly increased their uncertainty about the magnitude of escapement.

Our Bayesian approach could also be modified by adding parameters representing any biases. However, it is unlikely that the escapement data themselves contain enough information to reliably estimate the magnitude of any biases. In our example SE Alaskan pink stock, some (but not all) of the known biases were corrected prior to our use based on a calibration of aerial counts to weir counts (Dangel and Jones 1988; Jones et al 1998). Without such calibration studies, most escapement numbers are a relative abundance index rather than an estimate of absolute numbers.

Stream life is also a potential source of bias. While we have improved on past practice by modeling the decline in stream life over the course of the season (Dangel and Jones 1988; Perrin and Irvine 1990; Fukushima and Smoker 1997), we have not incorporated interannual fluctuation in the average stream life. Such fluctuations are well-documented (Ellis 1969; Dangel and Jones 1988; Bue et al. 1998), and their incorporation would undoubtedly increase uncertainty about escapement magnitude and timing. In sum, modifications to our Bayesian framework could be made to capture the additional uncertainty due to observer efficiency and stream life fluctuations. More useful, however, would be management agencies implementing prior recommendations (Quinn and Gates 1997; Bue et al. 1998; Hilborn et al. 1999) that representative streams be weired to allow annual estimates of these two factors.

The computation involved in generating Bayesian estimates of escapement can be discouraging. Obtaining point estimates of escapement is quicker in a maximum likelihood framework, since the required numerical function minimization is much faster than the numerical integration required for a Bayesian analysis. However, in calculating the uncertainty in the estimate, maximum likelihood estimates do not necessarily retain this advantage. The bootstrap and profile likelihood methodologies for calculating confidence intervals are not any less computationally intensive than an MCMC calculation of Bayesian credible intervals. Further, the rapid increase in cheap computing power and the development of simple numerical methods for generating samples from the posterior distribution (e.g., Gelman et al. 1995) have made Bayesian methods much more tractable.

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Chapter 3. Reconstructing historical northern Southeast Alaska pink salmon run, 1977-1998

Abstract

In this chapter, we defined major stocks and fisheries for pink salmon in the northern Southeast Alaska inside waters. The migration routes and residence times of these stocks were determined based on historical tagging data. We estimated the annual escapement for each stock by its peak escapement count and the escapement timing by the hierarchical Bayesian model developed in Chapter 1. A boxcar migration model was used to reconstruct the catch and abundance histories for these stocks from 1977 to 1998. Purse seine CPUE data were used to validate the reconstruction results. Sensitivity analyses were conducted to examine the influences of uncertainties in the migration routes and speed on the run reconstructions.

Introduction

Run reconstruction techniques based on catch, escapement and migration data can be used to reconstruct the abundance and migratory timing of salmon stocks, estimate stock-specific catch contributions and fishery-specific harvest rates (Starr and Hilborn 1988; Mundy et al. 1993; Templin 1996). We apply these techniques to the reconstruction of the abundance of the principal pink salmon stocks in the inside waters of northern Southeast Alaska (NSE) from 1977 to 1998.

Southeast Alaska is a narrow strip of land between the Gulf of Alaska and the Coast Range Mountains (Fig. I). This region comprises numerous large and small islands known as the Alexander Archipelago. It is one of the most productive areas in the world for five Pacific salmon species due to its diverse geographical conditions, heavy forest and abundant rainfall. Pink salmon is the most abundant salmon species in this region. It is the target species of the purse seine fishery, which takes about 95% (1980-1998 average) of the pink salmon caught.

Historical adult tagging studies have found a distinct separation of pink salmon stocks in northern (north of Sumner Strait) and southern Southeast Alaska areas (Nakatani et al. 1975; Hoffman 1982), and a separation of pink salmon migrating into NSE inside waters and the outer coast of NSE (there appears to be some movement of pink salmon from the outside coast into Hoonah Sound (Bill Davidson, ADF&G, Sitka, AK, pers. comm.)) (Nakatani et al. 1975; Hoffman 1982). Hence, we treat the pink salmon stocks originating from the NSE inside waters separately from other stock groups in Southeast Alaska.

The pink salmon fisheries (mainly purse seine) in the NSE inside waters are highly mixed-stock fisheries, especially in the two migration corridors, Icy Strait and Chatham Strait. Refined management of these fisheries requires a better understanding of the spatial and temporal dynamics of the major stocks traversing these fisheries. The reconstructions conducted in this research serve this purpose.

In this study, we define major pink salmon stocks (stock groups) in the NSE inside area. We make assumptions about the migration routes for these stocks based on historical tagging surveys. Major fishery areas are determined. We use Bayesian hierarchical escapement models as developed in Chapter 1 to estimate the escapement timing for these stocks. Necessary input data, such as catch and escapement, are compiled on a daily basis from Alaska Department of Fish and Game (ADF&G) databases. Finally, the run reconstructions are conducted using boxcar methods similar to those of Starr and Hilborn (1988).

This is the first run reconstruction work ever done for the NSE inside area. This research provides stock-specific spatial and temporal abundance, fishery-specific catch and harvest rate information. These results can be used in stock-recruitment analyses for determining optimal escapements for each stock, and can also be used for inseason management simulation.

Data and Methods

Run reconstruction method: the boxcar model

We adopt the multi-time-period reconstruction method proposed by Starr and Hilborn (1988). It assumes a boxcar-type migration. The basic assumption is that fish that enter the first fishery on the same day are treated as a daily "block", "cohort" or "clump". All fish of the same block move together through each fishery. Some fish of the same block might be caught along the way, and those fish escaping all the fisheries return to their natal streams for spawning. The run reconstruction works backwards in time for each block from the daily escapement to the daily entry. We use stock-specific escapement data and migration data to back-calculate the abundance and catch for each stock in each fishery within the season, thus providing stock-specific run size, run timing, catch and harvest rate estimates the manager needs.

The equations for the reconstruction are as follows:

The abundance after catch $N^*_{s,b,d,t}$ for a daily block of stock *s*, in its *b*th time period after entering its first fishery, at its time period *t* in the season, in the fishery *d*, is set as

$$(3.1) \quad N^*_{s,b,d,t} = N_{s,b+1,d',t+1}$$

where $N_{s,b+1,d',t+1}$ is the abundance before catch for a daily block of stock *s*, in its (b+1) th time period after entering its first fishery, at its time period $t+1$ in the season, in the fishery d' (*d* and d' might be the same or not).

A block can be identified by the entry date to the first fishery or its escapement date. Subscript *b* can be derived from subscript *t* and the entry or escapement dates. Subscript *d* can be derived from *b* and residence times. We keep all these subscripts for clarity.

The abundance after catch N^*_{s,B_s,D_s,T_s} before the block escaping the last fishery (at its last time period T_s in its last fishery D_s) is set to the daily escapements for that stock E_{s,T_s+1}

$$(3.2) \quad N^*_{s,B_s,D_s,T_s} = E_{s,T_s+1},$$

where B_s denotes the total residence time for stock *s*.

The abundance before catch $N_{s,b,d,t}$ for a daily block of stock *s* is calculated as

$$(3.3) \quad N_{s,b,d,t} = N^*_{s,b,d,t}(1 + C_{d,t} / N^*_{d,t}),$$

where $C_{d,t}$ is the daily catch for fishery *d*. The $N^*_{d,t}$ denotes the total daily abundance after catch of all stocks in fishery *d*, and is calculated by

(3.4) $N^*_{d,t} = \sum_{\{s\}}\sum_{\{b\}} N^*_{s,b,d,t}$.

The daily number of fish of stock *s* entering an entry fishery is calculated as

(3.5) $x_{s,t} = N_{s,1,d,t}$.

The fishery-specific harvest rate is

(3.6) $h_{d,t} = C_{d,t} / N_{d,t}$,

where

(3.7) $N_{d,t} = N^*_{d,t} + C_{d,t}$.

Reconstruction techniques require a wide variety of data for their input, including (i) stock-specific escapement; (ii) fishery-specific catch data and (iii) stock-specific migration route and speed data. The catch, effort and escapement data used in this chapter were obtained from the ADF&G Integrated Fisheries Database (Ben Van Alen, ADF&G, pers. comm.). Escapement data are sparse before 1980 (for estimating escapement timing). However, we included the years 1977 to 1979 along with 1980 to 1998 in the analysis because there were tagging surveys for pink salmon conducted from 1977 to 1980 (Hoffman 1982) in this area.

Definition of stocks

Before attempting run reconstructions, one needs to define the stocks, fisheries, and the migration routes. There are many definitions for the stock concept (Ricker 1954; Baker et al. 1996). For the purpose of this run reconstruction, we defined a stock as a geographic grouping of two or more stream spawning units that experience similar environmental influences and have similar migration routes and timing (Alexandersdottir 1987; Van Alen 2000).

Table 3.1 Stocks defined for pink salmon run reconstructions.

Stock		Migration		
(Abbreviation)	Components	Route	Run timing	Stream entry
Icy Strait/U. Chatham (ICY)	Icy Strait (including Homeshore (HOM)), Hawk Inlet, Howard Bay, Lynn Canal	Icy Strait/Upper Chatham and Lynn Canal	Early ~ Middle	07/20 ~ 08/ 15
Tenakee (TEN)	Tenakee Inlet	Icy Strait/Upper Chatham, Basket Bay, Tenakee Inlet	Early	07/20 ~ 07/30
Basket Bay (BAS)	Freshwater Bay, Basket Bay, Kelp Bay	Icy Strait/Upper Chatham, Freshwater Bay, Basket Bay, Kelp Bay	Middle	07/25 ~ 08/ 25
W. Admiralty (WAD)	West Admiralty Island	Icy Strait/Upper Chatham, West Admiralty	Middle ~ late	08/ 10 ~ 09/ 5
Peril Strait (PER)	Peril Strait	Icy Strait/Upper Chatham, Basket Bay, Peril Strait	Middle	08/ 1 ~ 08/ 31
L. Chatham (LCH)	East Baranof Island, West Kuiu Island	Lower Chatham	Middle ~ Late	08/ 10 ~ 09/15
O. Frederick (OFR)	Outer Frederick Sound	(i) Icy Strait/Upper Chatham, West Admiralty, Lower Chatham, Frederick Sound; (ii) Lower Chatham, Frederick Sound	Middle ~ Late	08/ 10 ~ 09/15
I. Frederick/ Seymour (IFS)	Inner Frederick, Seymour Canal (SEY)	(i) Icy Strait/Upper Chatham, West Admiralty, Lower Chatham, Frederick Sound; (ii) Lower Chatham, Frederick Sound	Early ~ middle	07/20 ~ 08/ 15
Stephens/Taku (STT)	Stephens Passage, Taku River	(i) Icy Strait/Upper Chatham, Stephens Passage; (ii) Icy Strait/Upper Chatham, West Admiralty, Lower Chatham, Frederick Sound, Stephens Passage	Early ~ middle	07/20 ~ 08/ 15

We defined 9 pink salmon stocks for the NSE inside area (Table 3.1, Fig. 3.1) based on their geographic locations, migration information obtained from historical tagging surveys (Nakatani et al. 1975; Hoffman 1982), escapement timing as estimated in a previous study (see "Escapement" section), as well as management unit information as defined by ADF&G.

Migration of pink salmon stocks

Migration routes and proportions

We use historical adult tagging data (Nakatani et al. 1975; Hoffman 1982) as the basis for determining the migration routes of pink salmon stocks in this region, which are shown in Table 3.1 and Figs. I, 3.1-3.2.

These tagging studies have shown large yearly variations in the migration routes for some stocks. For example, only a minor portion of Frederick Sound pink salmon (<0.9% for outer Frederick Sound, <2.5% for inner Frederick Sound) returned through two upper Chatham Strait release sites in the 1977 and 1978 tagging surveys (Larson 1979; Hoffman 1982). This might suggest that these two stocks returned mostly through lower Chatham Strait in these two years. However, 1980 recoveries from lower Chatham Strait releases show no movement of Frederick Sound stocks from lower Chatham (Hoffman 1981). In 1979 and 1980, there were substantial numbers of inner Frederick Sound pink salmon (11.7% for 1979 and 28.4% for 1980) returning via west Admiralty release sites (Hoffman 1980, 1981).

Because of the large yearly variation of the migration of pink salmon stocks, we do not attempt to fit the reconstruction models to the data to specific years with tagging information. Rather we try to capture the average behavior of the migration. This is achieved by specifying the values of the (backward) migration proportions, which are the proportions of a specific stock in a fishery on day $t+1$ that came from the alternative possible migration routes on day t. For example, we assumed that 30% of the I.

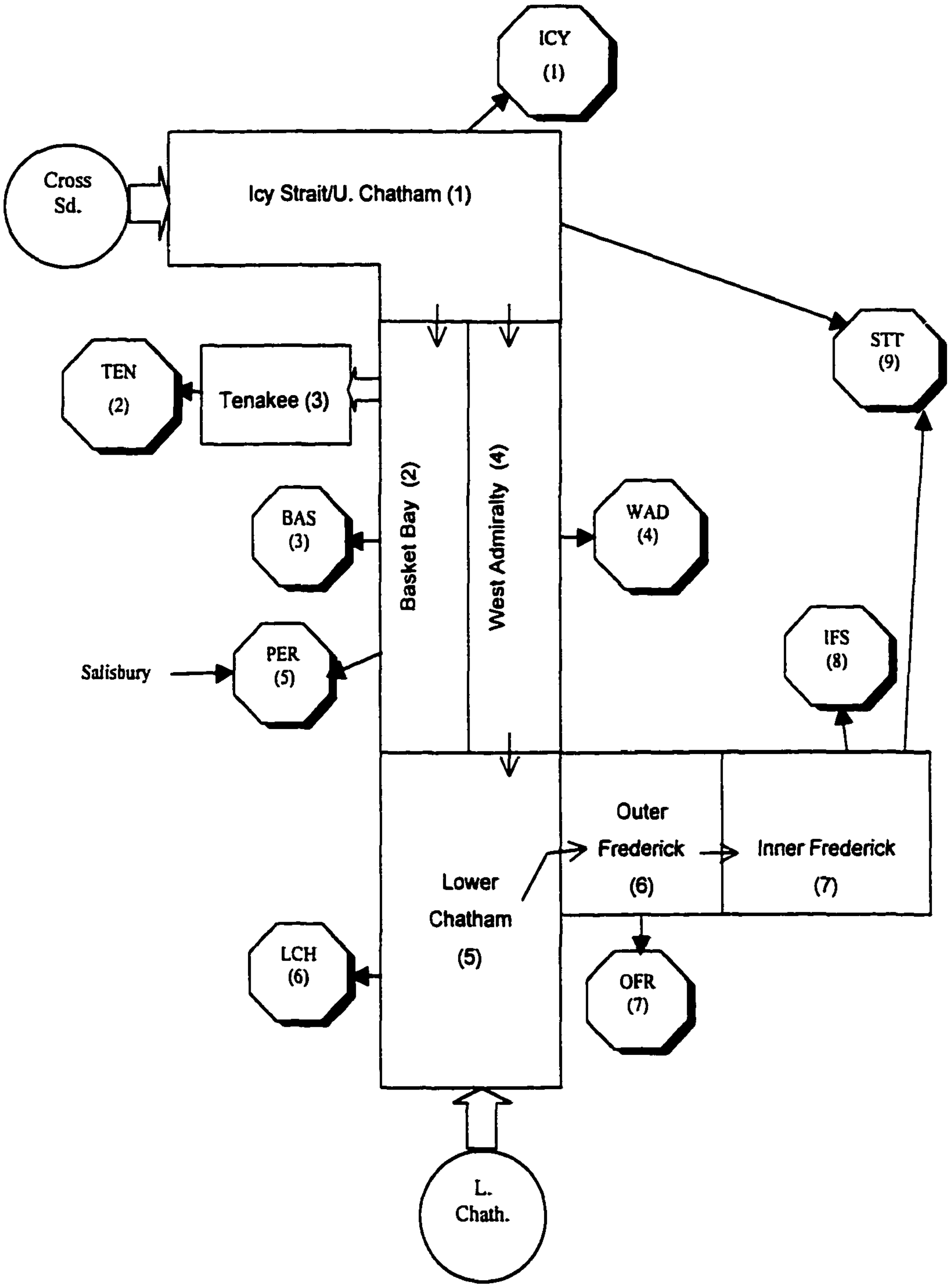


Fig. 3.1 Fisheries, stocks and migration scheme. The circles denote entrance points, octagons denote stocks and rectangles denote fisheries.

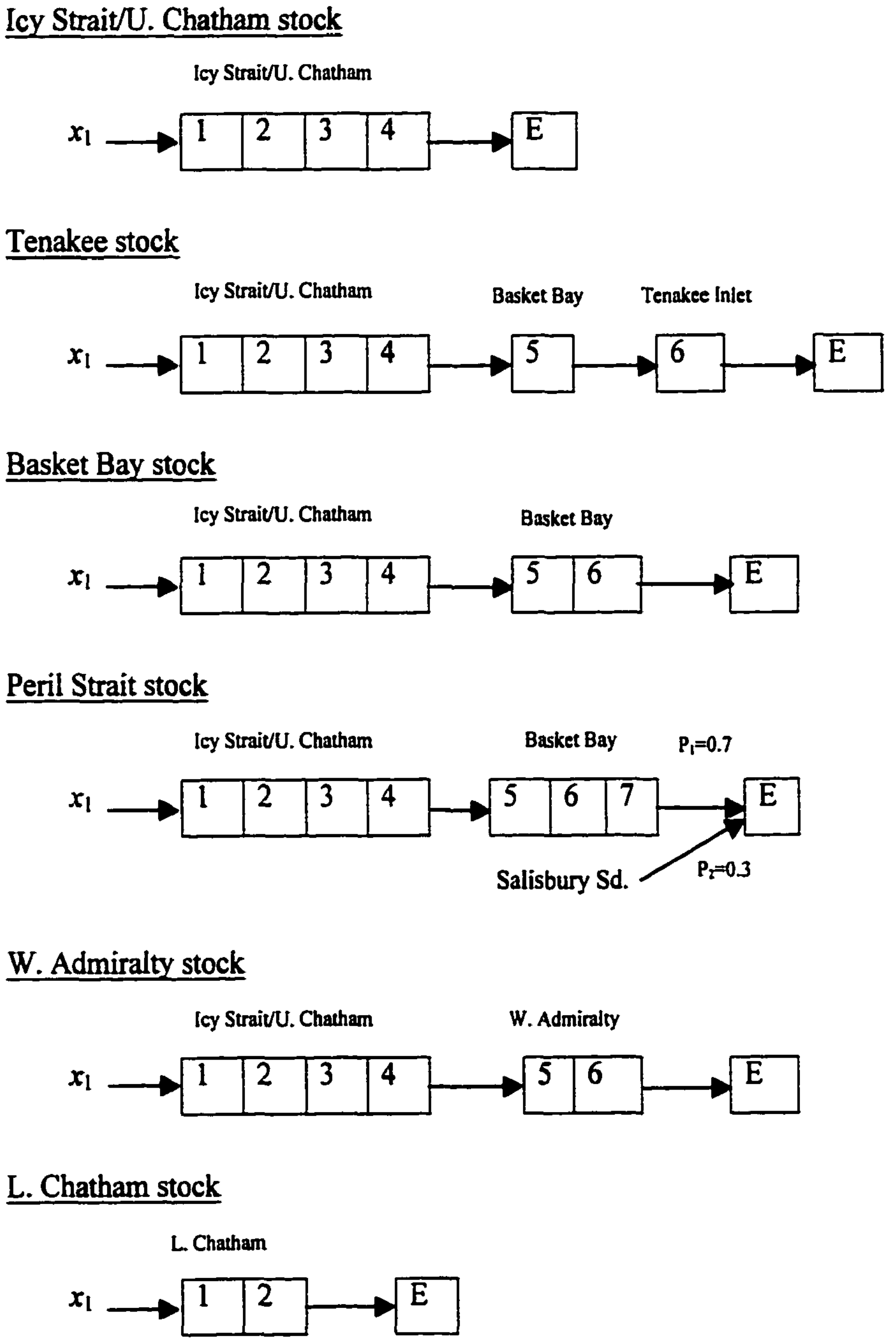
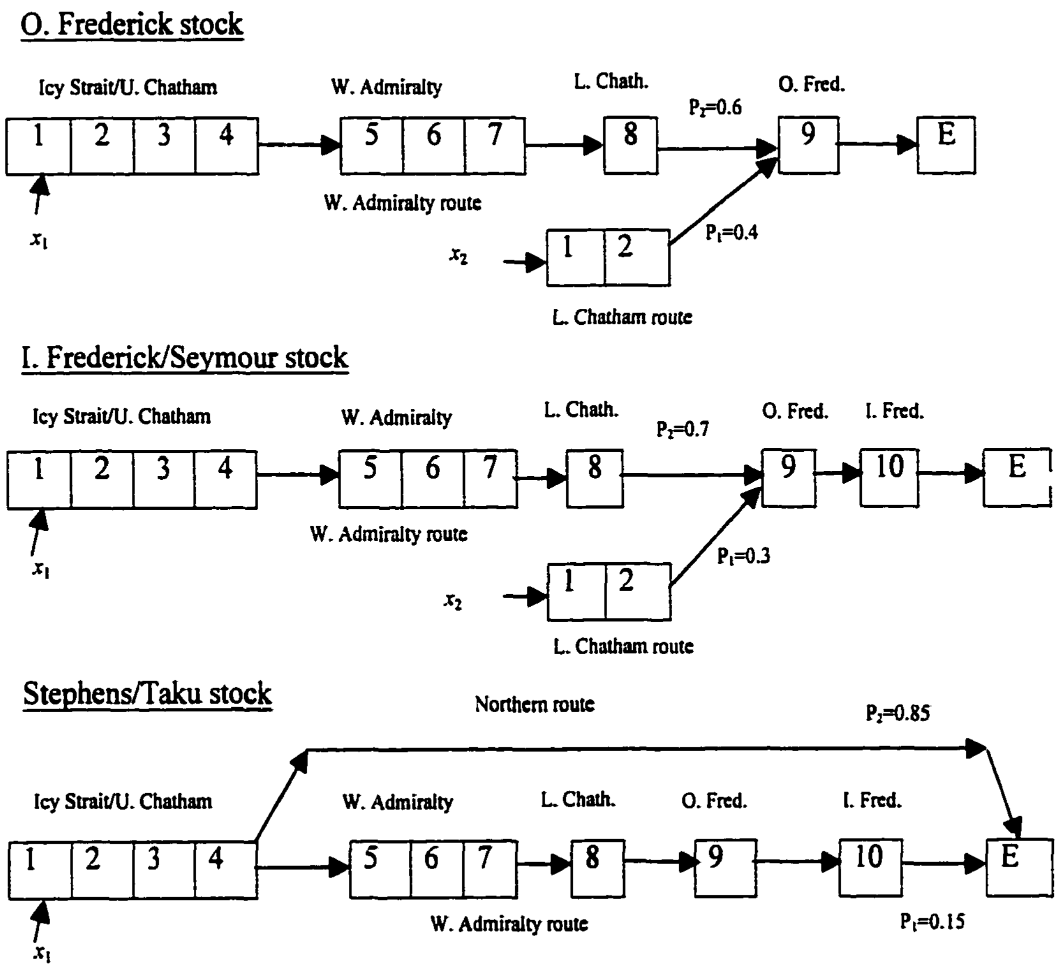


Fig. 3.2 The boxcar-type of migration of the nine stocks in daily blocks.

A square denotes one daily block. The adjacent squares represent all blocks of a stock in a fishery on different days. "x_1" denotes entry to Icy Strait and "x_2" denotes entry to L. Chatham Strait. "E" denotes the escapement area of a stock. "p_1, p_2" denote the migration proportions and p_2=1-p_1.

Fig. 3.2 (*continued*)



Frederick/Seymour stock entering the O. Frederick fishery on day $t+1$ arrived via the L. Chatham route (Fig. 3.2). The migration proportions set in the following (also see Fig. 3.2) are based on the major conclusions in Hoffman (1982), as well as local manager's beliefs about pink salmon in this region (ADF&G 2001; Ben Van Alen and Andy

McGregor, ADF&G, pers. comm.). Sensitivity analyses are conducted in the following section to examine the influence of these parameters.

Pink salmon enter the NSE inside waters through two entrances: Icy Strait and lower Chatham Strait (south of Point Gardner). Stocks distributed in the northern areas of this region (north of Frederick Sound) enter through Icy Strait, whereas the L. Chatham stock returns through the lower Chatham Strait entrance. Frederick Sound and Seymour Canal stocks enter through both entrances (Fig. I).

Here are some descriptions of migratory patterns of stocks with more complex migration routes (Figs. I, 3.1-3.2):

(1) The Tenakee stock is assumed to enter Tenakee Inlet directly or mill in the Basket Bay shoreline waters before returning to Tenakee Inlet (see Points 8 and 9 of "Management implications" section and Figure 9 in Hoffman (1982)).

(2) Similarly, the Basket Bay stock is assumed to migrate along the west side of Chatham Strait (see Points 8 and 31 of "Management implications" section and Figure 9 in Hoffman (1982)).

(3) Some portion of the Peril Strait stock may return directly from the outer coast through Salisbury Sound (Bill Davidson, ADF&G, Sitka, AK pers. comm.). For simplicity's sake, we do not include this route in the reconstructions. Only the branch returning through Chatham Strait is modeled. We assume that 70% of the escapement of Peril Strait stock on day t+1 comes from Chatham Strait on day t. This portion is assumed to have the same migration patterns as the Basket Bay stock (Fig. 3.2) (see Points 8 and 31 of "Management implications" section and Figure 10 in Hoffman (1982)).

(4) The O. Frederick (west of Pybus Bay) stock enters mostly through Icy Strait and migrates down along the W. Admiralty shoreline and lower Chatham Strait, before returning to Frederick Sound (called W. Admiralty route) (see Points 8, 16, 18, 23, 25 and 26 of "Management implications" section and Figure 6 in Hoffman (1982)). Some portion of this stock also returns via the lower Chatham Strait entrance (Nakatani et al. 1975). We assume that 40% fish of this stock in the O.

Frederick fishery on day *t*+1 returned from the lower Chatham Strait route on day *t* (Fig. 3.2).

(5) Most of the I. Frederick/Seymour stock returns via the W. Admiralty route (see Points 8, 16, 18, 23, 25 and 26 of "Management implications" section and Figure 7 in Hoffman (1982)); some portion of this stock also returns via the lower Chatham Strait entrance (Nakatani et al. 1975). We assume that 30% fish of this stock in the O. Frederick fishery on day *t*+1 return from the lower Chatham Strait route on day *t* (Fig. 3.2).

(6) Pink salmon of northern Stephens Passage return mostly through Icy Strait, upper Chatham and Lynn Canal (northern route) (see "Migration Patterns" section and Figure 8 in Hoffman (1982)). Pink salmon distributed in the Taku River and Snettisham drainage tributaries might return through either the northern or W. Admiralty route (see Points 19 of "Management implications" section and Figure 8 in Hoffman (1982)). Based on past tagging studies, we assume that 85% of the escapement of the Stephens/Taku stock on day *t*+1 returns via the northern route (Fig. 3.2).

For more details of the migration of the stocks, see "Definitions of Fisheries" section.

Residence times and holding times

Holding time is the time pink salmon spend milling at the mouth of the stream before ascending to the spawning area (Heard 1991). The holding time of all stocks was set to 5 days (see Templin et al. 1996) and it is deducted from the mean dates of stream entry to obtain the mean dates of escapement for the stocks (see "Escapement" section below).

Migration speed determines the residence time in a district (distance/speed); or the time a fish is exposed to a fishery. We used estimates of the migration speed of pink salmon in the NSE inside area from Nakatani et al. (1975). They calculated the migration rate of pink salmon recovered in their tagging study and gave an estimate of 20 miles/day (32 km/day). This is much faster than the value (4.67 miles/day (7.5 km/day)) used for Prince William Sound pink salmon by Templin (1995). Tarbox (1988) found similarly high migration rates, 20 - 40 km/day, for Cook Inlet pink salmon. The residence time of pink salmon in each fishery (see "Definition of Fisheries" section) are listed in Table 3.2 (also see Fig. 3.2). A sensitivity analysis is conducted to examine the effect of possible misspecification of migration speed on the reconstruction results.

Definition of Fisheries

We defined 7 fisheries for the NSE inside area based on their geographical locations and the migration traits of the related stocks that traverse these fisheries (Table 3.2; Figs. I, 3.1-3.2).

Table 3.2 Fishery definition and residence time of stocks in each fishery

Fishery	Definition (statistical districts and subdistricts)	Residence time (days)
Icy Strait/U Chatham	114,112-13,14,15,16,61,65	4
Tenakee	112-41 to 48	1
Basket Bay [a]	112-11,12,21,22,50	2
W. Admiralty [b]	112-17,18,19,67 to 90	3
L. Chatham [c]	109-10,11,20,51,52,61-63	2
O. Frederick	109-30 to 50	1
I. Frederick	110	1

Note:

[a] The Tenakee and Peril Strait stocks are assumed to spend one day and three days in the Basket Bay fishery, respectively

[b] The W. Admiralty stock is assumed to spend 2 days in the W. Admiralty fishery

[c] Fish of O. Frederick and I. Frederick/Seymour stocks using the W. Admiralty route are assumed to spend one day in the L. Chatham fishery

Here are some descriptions of four highly mixed-stock fisheries, which occur in the migration corridors of pink salmon destined to more inside waters.

Icy Strait/U. Chatham fishery: including Icy Strait and the fishing area in Chatham Strait north of Freshwater Bay (upper Chatham Strait). East Icy Strait pink salmon were observed to mill in the upper Chatham Strait area, whereas only a minimal portion of the Icy Strait/U. Chatham stock moves into middle Chatham ((see Points 4, 10 and 14 of "Management implications" section in Hoffman (1982))). To simplify the migration model, we treat the Icy Strait and the upper Chatham Strait region as one fishery.

There is an extreme amount of stock mixing in this area. All stocks except for that of lower Chatham Strait travel first through this area.

Basket Bay and W. Admiralty fisheries: The Basket Bay fishery includes Freshwater Bay, Basket Bay and Kelp Bay (Fig. I). This area is distinct from the W. Admiralty fishery according to past tagging survey findings (Hoffman 1982).

Tagging studies (Larson 1979; Hoffman 1980, 1981, 1982) found that fishing in the Basket Bay shore area harvests mainly pink salmon returning to Tenakee Inlet, Basket Bay shoreline, Peril Strait and Kelp Bay streams (these accounted for 89% of the total tag recoveries from a Basket Bay release in 1978 and 92% in 1979); only a minor portion of west Admiralty pink salmon (6% in 1978 and 3% in 1979) and pink salmon destined for other areas moved along this side (also see Points 8 and 31 of "Management implications" section and Figure 9 in Hoffman (1982)). Pink salmon stocks destined to more inside waters such as Frederick Sound, Seymour Canal and portions of southern Stephens Passage were observed to move mostly along the west Admiralty shoreline (Hoffman 1982).

Lower Chatham fishery: this is a major mixed-stock fishing area targeting on local stocks as well as stocks destined for Frederick Sound, Seymour Canal and portion of southern Stephens Passage (see Points 15, 17, 24 and 27 of "Management implications" section and Figure 6 in Hoffman (1982)).

Escapement

The run reconstruction needs escapement data in the form of escapement by time period for each stock, which can be calculated using the total escapement and the timing distribution for each stock.

Although the hierarchical Bayesian modeling approach of Chapter 1 might provide improved estimates for escapement and escapement timing for a stream spawning unit, data quality prevents us from providing escapement estimates for all streams in this region. Nevertheless, we were able to obtain stream entry estimates for 25 streams, at least one stream for each stock except for the Stephens/Taku stock, for which we use the drift gillnet catch timing to estimate the escapement timing (details below). For 4 stocks, we have entry estimates for over three streams.

Fig. 3.3 shows that the entry timing estimates (mean date of arrival, M_y) are very similar for the streams belonging to the same stock, but differ a lot among stocks. An ANOVA on the estimates of annual mean dates of arrival confirmed this observation (Table 3.3). The principal effects found by the ANOVA were the stock areas and years (1977-1998). Streams were a nested factor within area. All three factors are highly significant, but the stock area factor explains most (76%) of the variation in the estimates of M_y (Table 3.3). Therefore we used the average values of annual mean dates of arrival M_y (minus the holding time) and the average of the standard deviations of the mean dates S of those streams for a stock as the stock escapement timing estimates (Table 3.4).

Table 3.3 ANOVA summary

Source	Df	SS	MS	F	P-Value
Stock area	7	67638.2	9662.6	637.5	0.0000
Year	21	1300.3	61.9	4.1	0.0000
Stream	17	12357.4	726.9	48.0	0.0000
Residuals	504	7639.7	15.2		
Total	549	88935.6			

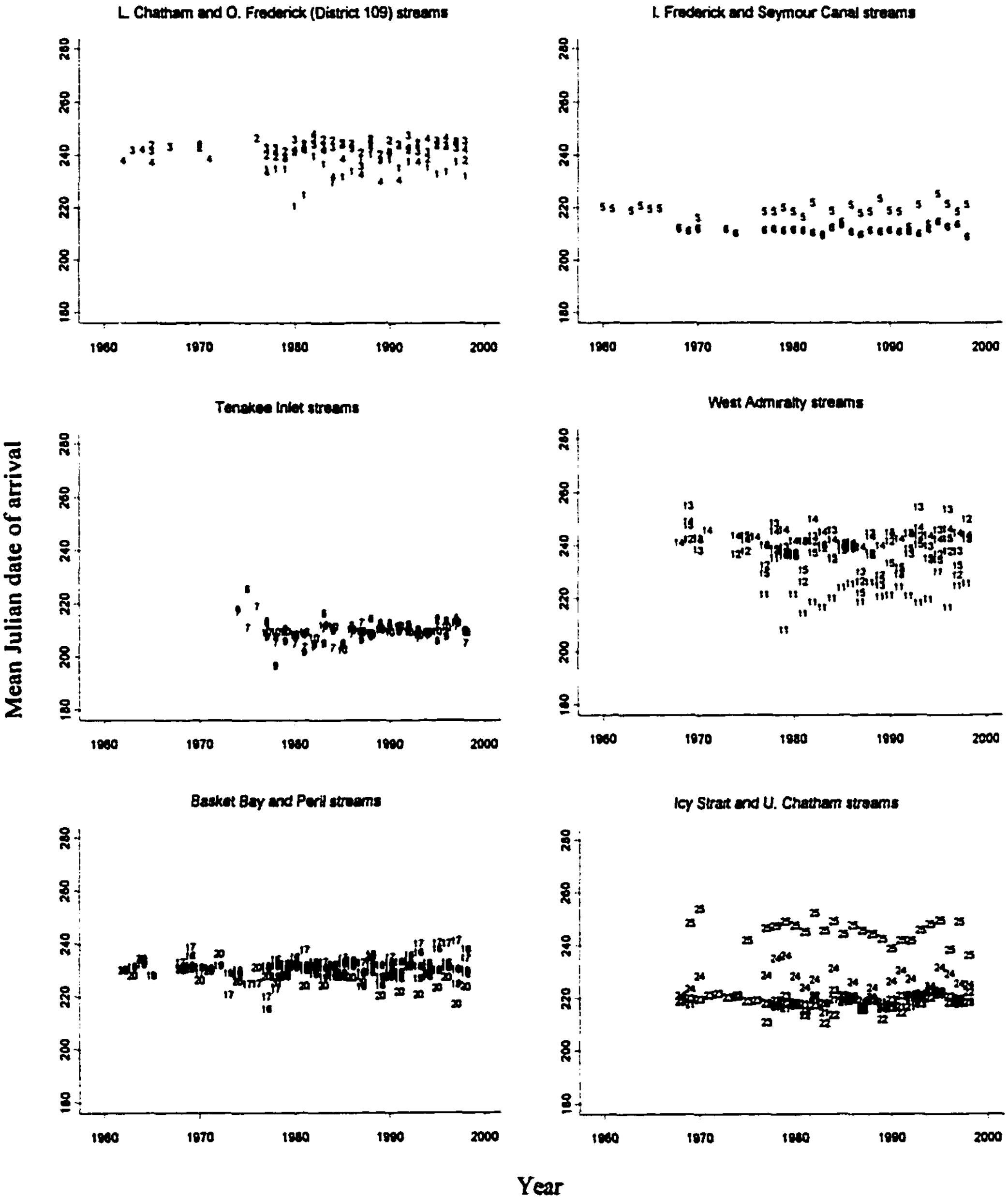


Fig. 3.3 Annual mean (Julian) dates of arrival for streams in different areas.

Listed below are the number, statistical district, subdistrict and the name of each stream appear on the figure: 1. 109-10-Sashin Ck P Walter N; 2. 109-62-Alecks Creek; 3. 109-30-Little Pybus Bay Ck; 4. 109-45-Security Bay Creek; 5. 110-32-Chuck R Windham Bay; 6. 111-17-King Salmon River; 7. 112-47-Long Bay Head; 8. 112-47-Seal Bay; 9. 112-42-Kandashan Creek; 10. 112-48-Big Goose

Creek; 11. 112-17-Marble Creek; 12. 112-19-Wilson River; 13. 112-73-Weir Ck S Arm Hood B; 14. 112-80-Chaik Bay Creek; 15. 112-90-Whitewater Creek; 16. 112-12-N of Basket Bay; 17. 112-12-White Rock Creek; 18. 113-58-Hoonah Sound N Head; 19. 113-57-Fick Cove Head; 20. 113-57-Patterson Bay W Head; 21. 112-13-Wukuklook; 22. 112-13-Iyouktug Creek; 23. 114-34-Humpback Creek; 24. 112-65-Greens Creek; 25. 114-25-Homeshore Creek.

Table 3.4 Average stream entry estimates for each stock (or substock), 1977-1998, estimated by the M_y-S model of Chapter 1 using the same settings as for the Kadashan Creek stock. The μ_m is the historical average of the annual mean (Julian) dates of arrival.

	Stock									
Parameters	ICY	HOM	TEN	BAS	WAD	PER	LCH	OFR	IFR	SEY
μ_m	220.4	246.0	209.9	231.6	240.2	230.4	243.6	242.0	219.0	211.9
S	16.6	28.2	15.3	19.0	18.2	15.9	16.7	12.3	14.4	13.1
M_{1977}	219.3	247.0	210.9	218.3	236.1	230.4	240.8	238.7	219.0	211.9
M_{1978}	222.6	247.9	205.4	229.1	243.3	228.8	240.2	242.3	219.0	212.4
M_{1979}	223.3	249.5	209.5	231.2	240.3	230.5	242.1	239.5	220.6	211.9
M_{1980}	221.0	248.1	207.8	234.2	238.4	232.5	241.9	244.4	219.0	212.1
M_{1981}	218.1	245.6	206.4	234.6	235.6	229.1	244.7	243.2	216.9	211.9
M_{1982}	221.8	252.8	205.8	229.3	243.6	232.4	246.3	246.6	222.3	210.9
M_{1983}	215.7	246.0	211.7	232.5	241.5	228.1	246.4	243.1	210.1	209.8
M_{1984}	222.3	249.7	209.5	228.7	240.1	231.8	246.0	238.1	219.3	212.8
M_{1985}	220.2	244.8	204.6	234.0	240.2	230.5	245.2	242.0	214.9	214.0
M_{1986}	222.0	248.1	211.0	232.6	240.7	231.6	244.9	243.6	221.4	211.1
M_{1987}	217.3	246.0	210.2	228.9	230.1	228.4	241.5	234.8	218.5	210.2
M_{1988}	221.1	244.7	210.4	231.6	241.0	234.8	246.5	244.4	219.0	211.9
M_{1989}	216.2	242.9	211.7	225.3	230.8	227.0	240.9	234.6	224.0	211.4
M_{1990}	220.1	239.3	211.6	232.5	241.7	231.3	245.9	241.8	219.3	211.9
M_{1991}	221.0	242.4	211.3	227.7	233.7	228.6	244.5	237.9	219.0	211.2
M_{1992}	221.7	242.3	211.0	235.5	241.7	232.6	242.6	245.6	213.0	211.4
M_{1993}	220.2	246.2	209.2	238.9	246.8	226.9	245.2	240.2	221.7	210.6
M_{1994}	223.2	248.6	209.3	229.3	239.0	231.4	239.2	244.2	214.1	212.3
M_{1995}	224.9	249.9	210.9	239.7	240.4	228.2	244.5	245.6	225.8	215.2
M_{1996}	222.0	238.8	210.9	237.0	245.7	230.2	244.0	245.5	221.9	213.2
M_{1997}	220.7	249.4	213.7	236.1	236.5	224.4	245.6	244.5	219.0	214.2
M_{1998}	221.4	236.6	209.0	236.7	245.3	228.0	238.6	244.1	221.8	209.4

Table 3.5 Annual escapement (×1000) for each stock and for all stocks combined, 1977-1998

Year	Stock									
	ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT	Total
1977	2,058	549	604	417	500	1,028	318	1,065	805	7,344
1978	778	1,452	585	371	836	948	289	1,471	488	7,218
1979	1,574	506	762	740	631	1,300	628	2,366	1,214	9,720
1980	939	791	295	557	370	547	397	1,370	764	6.029
1981	1,632	720	493	430	456	591	374	1,196	957	6,850
1982	1,417	971	524	644	582	1,111	739	2,439	1,298	9,726
1983	1,811	1,230	383	673	634	798	403	1,647	1,395	8,974
1984	1,483	649	491	529	689	995	656	2,294	1,034	8,820
1985	4,994	1,738	839	858	655	1,803	1,213	3,930	2.131	18.162
1986	579	1,576	412	536	383	1,138	941	1,374	473	7,412
1987	1,439	526	453	370	556	560	882	3,757	1,732	10,276
1988	802	804	402	297	402	987	452	1,581	688	6,415
1989	1,818	839	630	718	497	979	1,179	3,287	947	10,894
1990	1,409	774	448	606	574	853	802	2,982	842	9,291
1991	1,281	1,988	641	554	743	1,370	1,577	3,200	1,033	12,389
1992	1,094	1,010	450	525	833	1,373	1,330	3,666	1,509	11,789
1993	1,579	1,380	733	652	1,129	1,551	1,146	2,193	346	10,710
1994	2,370	1,581	1,040	776	1,108	2,247	1,672	4,482	3,042	18,319
1995	2,157	1,048	687	450	280	1,763	754	1,418	589	9,145
1996	518	1,305	613	841	733	3,322	1,845	2,356	1,800	13,332
1997	3,241	2,257	1,238	541	672	1,631	1,269	3,286	1,055	15.190
1998	731	1,325	724	1,409	1,058	2,036	1,439	3,285	1,875	13,884
Mean	1,623	1,137	611	613	651	1,315	923	2,484	1,183	10,540

The total escapement (Table 3.5) for a stock was calculated using a method similar to that ADF&G uses to calculate district escapement indices: summing the peak counts to all large streams (with a peak count greater than 10,000) within a stock, plus the peak counts to all small streams within a stock, plus an expansion for streams not surveyed each year in a stock. The expansion is calculated by the average peak count to all small streams times the number of streams not surveyed within a stock. An estimate of total escapement of a stock is obtained by expanding the sum of the peak counts just obtained by a factor of 2.5 (ADF&G 1997).

The daily escapement estimates of the stocks other than the Stephens/Taku stock are calculated by the total annual escapement estimates in Table 3.5 multiplied by the escapement timing curves formed from the HBM timing estimates in Table 3.4 (see Chapter 1, Eq. 1.2).

Table 3.6 Beta distribution parameter estimates used to calculate the daily escapements for the Stephens/Taku stock, 1977-1998

Year	Alpha	Beta	Year	Alpha	Beta
1977	7.22	19.34	1988	13.58	13.82
1978	4.78	11.84	1989	8.40	23.54
1979	9.12	21.18	1990	10.24	13.68
1980	9.20	14.32	1991	10.29	18.53
1981	9.23	18.95	1992	12.54	17.09
1982	11.32	16.76	1993	11.94	24.75
1983	10.62	17.32	1994	30.74	33.33
1984	6.65	12.12	1995	9.35	17.03
1985	12.73	23.01	1996	13.65	28.78
1986	9.01	13.39	1997	4.49	10.32
1987	16.53	30.78	1998	11.27	16.90

We use a beta distribution curve (Hilborn et al. 1999) to fit the weekly catch data for district 111 (Stephens Passage) drift gillnet each year. The two parameters of the beta distribution estimated for each year are listed in Table 3.6. These curves are shifted 3 days ahead to take into account the traveling time between escapement and catch. We then use these curves and the estimates of total annual escapement (Table 3.5) to calculate the daily escapements for the Stephens/Taku stock each year.

Catch and effort

The run reconstructions need catch data in the form of catch by time period for each fishery. Catch in the ADF&G Commercial Catch database are organized by fishery opening for each subdistrict. We estimate daily catch as the catch per opening divided by the number of days opened for each opening and subdistrict. The total daily catch for a fishery is the sum of daily catch for all component sub-districts (Table 3.2) of that fishery.

About 95% (1978-1998 average) of the catch of pink salmon is taken in purse seine fisheries. So, only purse seine catch are included in this analysis and in Chapter 4. Table 3.7 shows the annual purse seine catch for each fishery and the total annual catch for all fisheries from 1977 to 1998.

We use purse seine catch per unit effort (CPUE) data to validate the run reconstruction results. In order to obtain daily CPUE for each fishery, we need to obtain daily effort for that fishery. We first calculate the average effort (number of boats) for an opening (total effort in number of boat days per opening divided by the number of days opened), and this is treated as the daily effort for that opening and subdistrict. Then the total daily effort for a fishery is the sum of daily effort for all sub-districts for that fishery.

Finally, daily CPUE for a fishery is the daily catch divided by daily effort for that fishery. Weekly Icy Strait troll CPUE's (troll catch/#boat days) are also calculated and compared with the abundance patterns of the Icy Strait/U. Chatham fishery.

Results

Run reconstructions

We obtained stock-specific daily and total stock sizes, catches and harvest rates by fishery for pink salmon from 1977 to 1998 from the reconstructions.

Based on these results, stock sizes have increased for all the stocks since 1977 (Fig. 3.4 and Table 3.8). Total stock size showed a peak of over 30 million fish in 1985, and the 1994 abundance of close to 50 million is the highest. Stocks on Chatham Strait streams tend to be the smallest of those in NSE inside waters.

Table 3.7 Annual purse seine catch (×1000) for each fishery and all fisheries combined, 1977-1998

	Fishery							
Year	Icy Strait/U. Chatham	Tenakee Inlet	Basket Bay	W. Admiralty.	L. Chatham	O. Frederick	I. Frederick	Total
1977	0	0	0	28	0	0	0	28
1978	0	1,649	0	205	1	0	480	2,334
1979	91	140	6	1,055	137	95	95	1,617
1980	106	6	111	407	123	1	99	853
1981	1,328	145	64	109	21	263	83	2,012
1982	3,550	1,366	531	1,681	95	2,563	550	10,335
1983	1,074	863	124	570	0	183	264	3,078
1984	814	198	124	1,214	440	341	140	3,270
1985	4,648	976	1,398	2,621	1,377	2,574	594	14,188
1986	127	88	2	470	2	0	100	790
1987	1,762	520	0	77	247	909	96	3,609
1988	109	322	5	497	101	0	242	1,276
1989	3,211	1,659	897	1,013	1,399	2,447	818	11,444
1990	1,009	319	71	1,553	523	319	276	4,069
1991	3,796	1,234	2,048	3,144	1,914	2,652	1,203	15,991
1992	2,083	887	264	4,236	1,612	2,384	846	12,311
1993	4,932	3,538	1,686	3,621	1,475	181	550	15,983
1994	5,768	4,702	925	8,265	2,120	7,050	1,586	30,416
1995	269	494	2	2,847	3	2	133	3,750
1996	2,029	534	198	2,338	1,542	888	285	7,813
1997	4,013	1,590	0	2,264	562	1	767	9,195
1998	1,402	1,874	678	4,109	2,000	868	318	11,248

The region-wide average annual harvest rate is moderate over time with a value of 33.4% (Table 3.9). 1982, 1989 and the early 90's (with the exception of 1990) saw higher harvest rates in the range of 51% to 62.5%. The harvest rates for all other years range from 0.4% to 45%. Stocks along the west shore of Chatham Strait (Tenakee, Basket Bay and Peril) and stocks in Frederick Sound and Seymour Canal have the highest harvest rates (historical mean ranging from 28% to 41%). The historical mean harvest rates of other stocks are less than 27%.

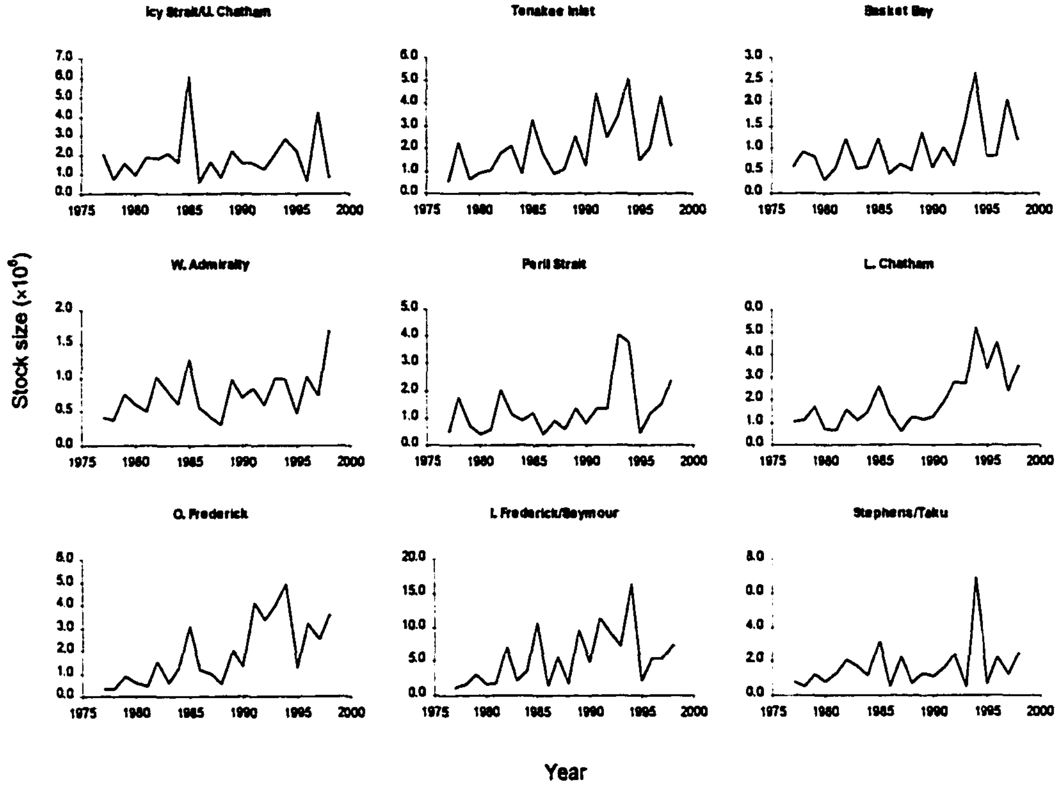


Fig. 3.4 Annual stock size estimates (×10^6) for each stock, 1977-1998.

The differences in the harvest rates are partially caused by management policies. Fishing effort is directed by managers to near terminal areas of a stock and away from the highly mixed-stock, usually the more outside entrance areas, such as Icy Strait and Chatham Strait. The stocks that only traverse these areas, such as Icy Strait/U. Chatham and Stephens/Taku stocks, receive less fishing effort, and have lower harvest rates. The stocks that are directly targeted and that migrate through several fisheries (e.g., the Basket Bay fishery targets on Tenakee, Basket Bay and Peril stocks) have higher harvest rates.

Table 3.8 Annual stock size estimates (×1000) for each stock and all stocks combined, 1977-1998

	Stock									
Year	ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT	Total
1977	2,058	549	604	417	500	1,044	322	1,073	805	7,372
1978	778	2,294	929	371	1,778	1,063	316	1,533	489	9,552
1979	1,596	628	818	750	711	1,673	861	3,056	1,245	11,338
1980	960	895	307	611	386	725	585	1,624	792	6,883
1981	1,922	1,033	580	502	584	624	435	1,879	1,304	8,862
1982	1,846	1,782	1,229	1,014	2,042	1,543	1,491	7,038	2,076	20,060
1983	2,052	2,083	543	787	1,104	1,072	607	2,113	1,690	12,052
1984	1,651	883	595	605	884	1,459	1,246	3,581	1,187	12,090
1985	6,077	3,238	1,225	1,254	1,150	2,585	3,064	10,569	3,187	32,350
1986	593	1,758	435	551	413	1,360	1,124	1,477	490	8,202
1987	1,648	884	641	407	896	568	978	5,634	2,229	13,885
1988	818	1,105	513	304	591	1,222	566	1,832	740	7,691
1989	2,220	2,561	1,341	973	1,347	1,134	1,997	9,465	1,301	22,338
1990	1,583	1,248	569	697	789	1,225	1,311	4,871	1,068	13,360
1991	1,579	4,412	1,027	854	1,372	1,968	4,118	11,402	1,648	28,379
1992	1,252	2,473	624	590	1,349	2,776	3,352	9,273	2,411	24,100
1993	2,109	3,432	1,603	990	4,043	2,718	4,029	7,274	495	26,693
1994	2,825	5,073	2,668	979	3,765	5,191	4,916	16,420	6,898	48,736
1995	2,233	1,442	842	462	440	3,366	1,265	2,201	645	12,895
1996	632	2,049	831	1,017	1,178	4,542	3,165	5,484	2,248	21,146
1997	4,250	4,316	2,077	739	1,512	2,383	2,500	5,359	1,249	24,386
1998	794	2,095	1,190	1,687	2,408	3,533	3,636	7,353	2,436	25,131
Mean	1,885	2,102	963	753	1,329	1,990	1,904	5,478	1,665	18,068
%	10.4%	11.6%	5.3%	4.2%	7.4%	11.0%	10.5%	30.3%	9.2%	100.0%

Table 3.9 Annual harvest rate estimates for each stock and all stocks combined, 1977-1998

Year	Stock									
	ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT	Total
1977	0.0%	0.0%	0.0%	0.0%	0.0%	1.5%	1.4%	0.7%	0.0%	0.4%
1978	0.0%	36.7%	37.1%	0.0%	53.0%	10.8%	8.7%	4.1%	0.2%	24.4%
1979	1.3%	19.5%	6.8%	1.3%	11.3%	22.3%	27.1%	22.6%	2.6%	14.3%
1980	2.2%	11.6%	3.8%	8.9%	4.0%	24.6%	32.1%	15.6%	3.5%	12.4%
1981	15.1%	30.3%	15.0%	14.3%	22.0%	5.3%	14.0%	36.3%	26.6%	22.7%
1982	23.3%	45.5%	57.4%	36.5%	71.5%	28.0%	50.4%	65.3%	37.5%	51.5%
1983	11.7%	41.0%	29.5%	14.6%	42.6%	25.6%	33.7%	22.0%	17.5%	25.5%
1984	10.1%	26.5%	17.6%	12.5%	22.1%	31.8%	47.3%	35.9%	12.9%	27.0%
1985	17.8%	46.3%	31.5%	31.6%	43.1%	30.2%	60.4%	62.8%	33.1%	43.9%
1986	2.5%	10.3%	5.4%	2.8%	7.2%	16.4%	16.3%	7.0%	3.4%	9.6%
1987	12.7%	40.4%	29.3%	9.1%	38.0%	1.4%	9.8%	33.3%	22.3%	26.0%
1988	2.0%	27.3%	21.7%	2.3%	32.0%	19.2%	20.1%	13.7%	7.0%	16.6%
1989	18.1%	67.2%	53.0%	26.3%	63.1%	13.6%	41.0%	65.3%	27.2%	51.2%
1990	11.0%	37.9%	21.3%	13.0%	27.3%	30.3%	38.8%	38.8%	21.1%	30.5%
1991	18.8%	54.9%	37.5%	35.2%	45.8%	30.4%	61.7%	71.9%	37.3%	56.3%
1992	12.6%	59.2%	27.9%	11.0%	38.3%	50.5%	60.3%	60.5%	37.4%	51.1%
1993	25.2%	59.8%	54.2%	34.1%	72.1%	42.9%	71.5%	69.8%	30.2%	59.9%
1994	16.1%	68.8%	61.0%	20.7%	70.6%	56.7%	66.0%	72.7%	55.9%	62.4%
1995	3.4%	27.3%	18.4%	2.7%	36.4%	47.6%	40.4%	35.6%	8.7%	29.1%
1996	18.1%	36.3%	26.3%	17.3%	37.8%	26.9%	41.7%	57.0%	19.9%	36.9%
1997	23.7%	47.7%	40.4%	26.7%	55.5%	31.6%	49.2%	38.7%	15.5%	37.7%
1998	8.0%	36.7%	39.1%	16.5%	56.0%	42.4%	60.4%	55.3%	23.0%	44.8%
Mean	11.5%	37.8%	28.8%	15.3%	38.6%	26.8%	38.7%	40.2%	20.1%	33.4%

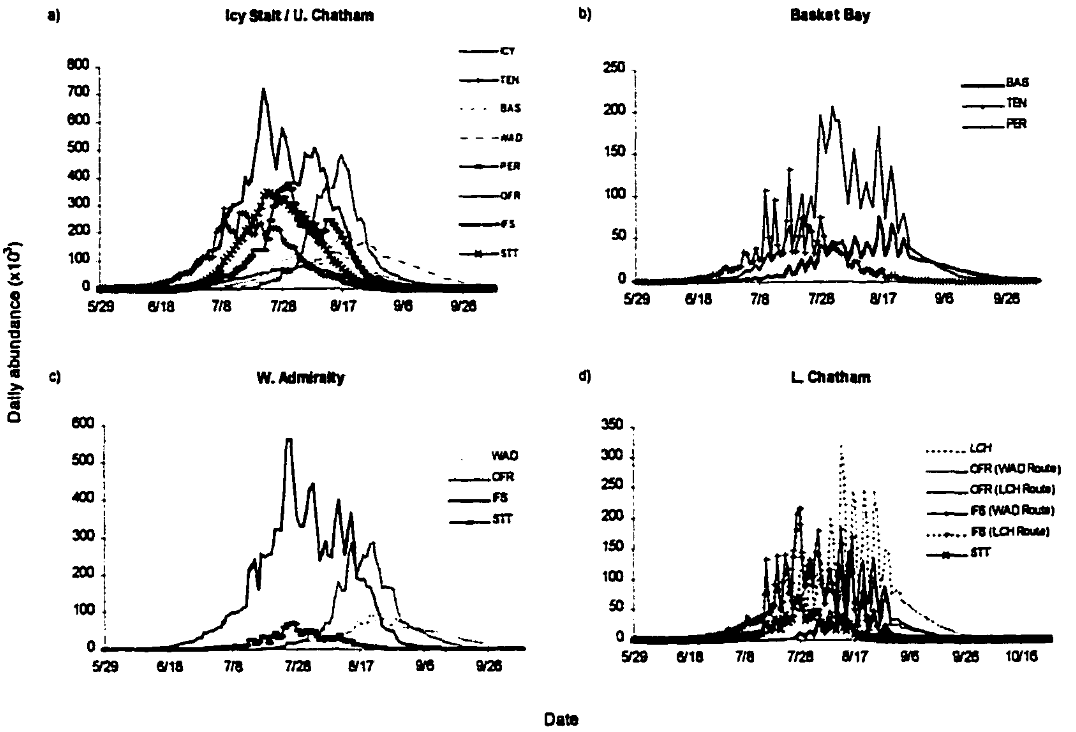


Fig. 3.5 Daily abundance of different stocks in four corridor fisheries in 1998.

Fig. 3.5 shows the daily abundance patterns of pink salmon stocks in four highly mixed-stock fisheries for 1998. In the Icy Strait/U. Chatham area, stocks in Tenakee Inlet, inner Frederick Sound, Seymour Canal, Peril Strait, and Stephens Passage predominate before August (Fig. 3.5*a*). In August, late-run (segment) stocks, such as W. Admiralty, Basket Bay, and O. Frederick stocks, are predominant in this area.

In the Basket Bay fishing area (Fig. 3.5*b*), the Tenakee stock is most abundant in the early season, whereas Basket Bay and Peril stocks dominate this area after late July. In the west Admiralty area (Fig. 3.5*c*), the I. Frederick/Seymour stock dominates the early and middle season and O. Frederick and local W. Admiralty stocks are abundant in the late season after late July. In the lower Chatham area (Fig. 3.5*d*), I. Frederick/Seymour and Stephens/Taku stocks dominate the early season before late July and fish destined for district 109 (lower Chatham Strait and O. Frederick Sound) control the late season.

Fig. 3.6 illustrates the inseason migration and abundance dynamics for the I. Frederick/Seymour stock. Because of migration and harvest, the abundance decreases and timing becomes successively later as a stock passes from one fishing area to another.

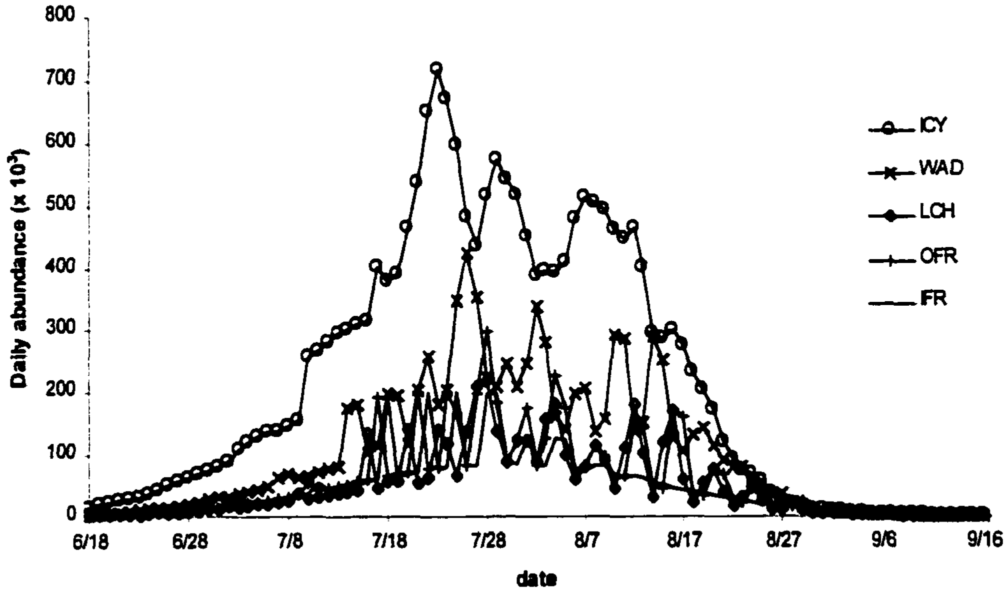


Fig. 3.6 Daily abundance of the I. Frederick/Seymour stock in several fisheries it traverses in 1998.

The run timing of different stocks entering Icy Strait differs substantially in a given year (Fig. 3.7). For example, the Tenakee stock was estimated to enter Icy Strait 33 days earlier than the W. Admiralty stock in 1998.

The variation in run timing for an individual stock for different years is not as large as the differences among different stocks in a single year (Fig. 3.8). For the Tenakee

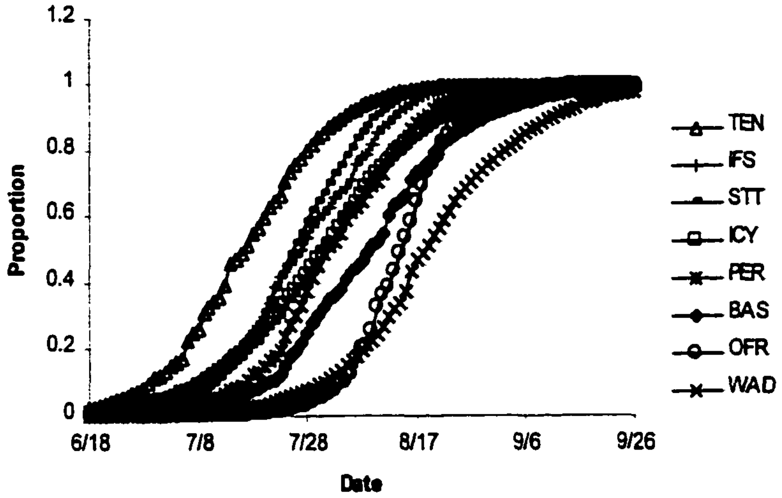


Fig. 3.7 Cumulative entry into the Icy Strait/U. Chatham fishery by different stocks in 1998.

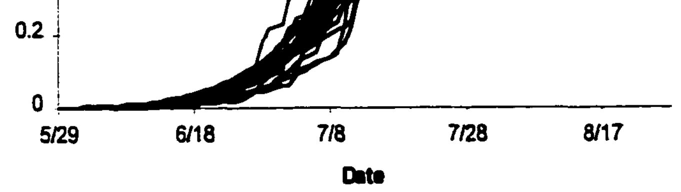


Fig. 3.8 Cumulative entry into the Icy Strait/U. Chatham fishery by the Tenakee Inlet stock, 1977-1998.

stock, the earliest 50% date of entry was July 10 in 1994 and the latest was July 18 in 1997, a difference of only 9 days. In contrast, differences in timing for some stocks could be over 30 days (Fig. 3.7).

Validation

In order to validate our run reconstruction results, we compared them with three somewhat independent indicators of pink salmon abundance: purse seine fishery CPUE, troll CPUE in district 114 (Icy Strait), and annual estimates of the number of recruits per spawner by stock (if these were unusually high or low, this might indicate an error in estimating spawners or recruits). These validations are somewhat limited because the CPUE data only reflect the abundance of the stock mixture for a fishery. No stock-specific information is available from such data. Although the tagging surveys provide some stock composition information, they were conducted at several limited and different locations each year (Hoffman 1982). These data do not provide a complete picture of the entire migration system each year, and difficult to compare among years.

Comparison of timing patterns of abundance with those of purse seine and troll CPUE

Our estimates of daily abundance basically match temporal patterns in purse seine CPUE for most fisheries and most years (Figs. 3.9-3.10). Estimated Icy Strait daily abundance also roughly matches CPUE in the district 114 troll fishery for the early season (Fig. 3.10), but does not correspond well later in the season, when troll CPUE drops faster than our estimated abundance. This may reflect a shift in the behavior of the troll fleet, possibly targeting coho rather than pinks as the season progresses. Overall, the run timing of the stock mixture derived from the reconstructions for each fishery appears reasonable.

Recruits per spawner (R/S)

The values of recruits per spawner can be used to evaluate the reconstruction results. Because we use the same set of migration data to conduct the run reconstruction

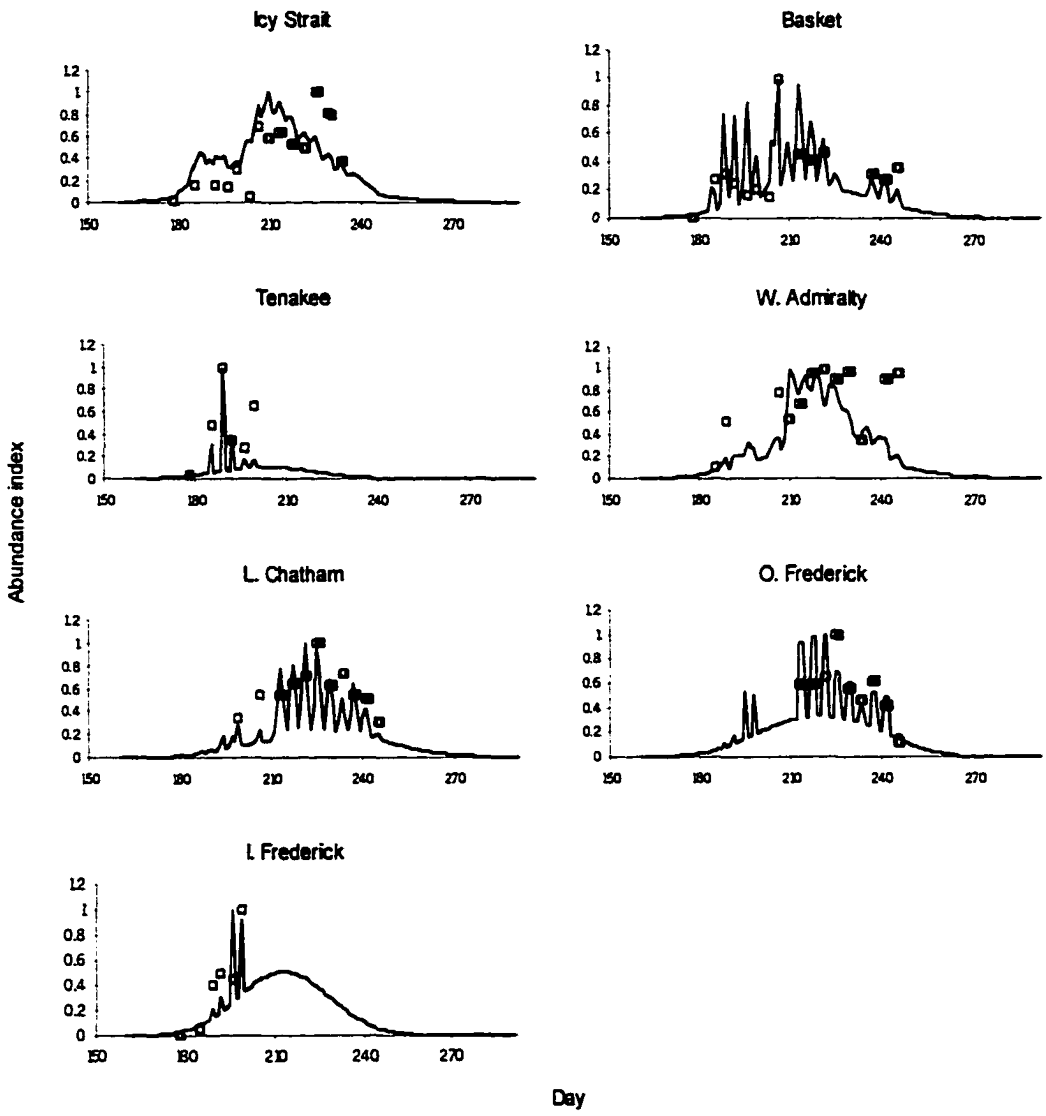


Fig. 3.9 Comparison of the daily abundance (line) and purse seine CPUE (squares) timing patterns for each fishery in 1993.

The daily abundance curve is obtained by scaling the daily abundances for a fishery by its peak abundance. The CPUE data for a fishery are scaled by its maximum CPUE to obtain the timing curve. The fishing effort of the Basket Bay fishery does not include the fishing effort of Hidden Falls for it targets chum salmon.

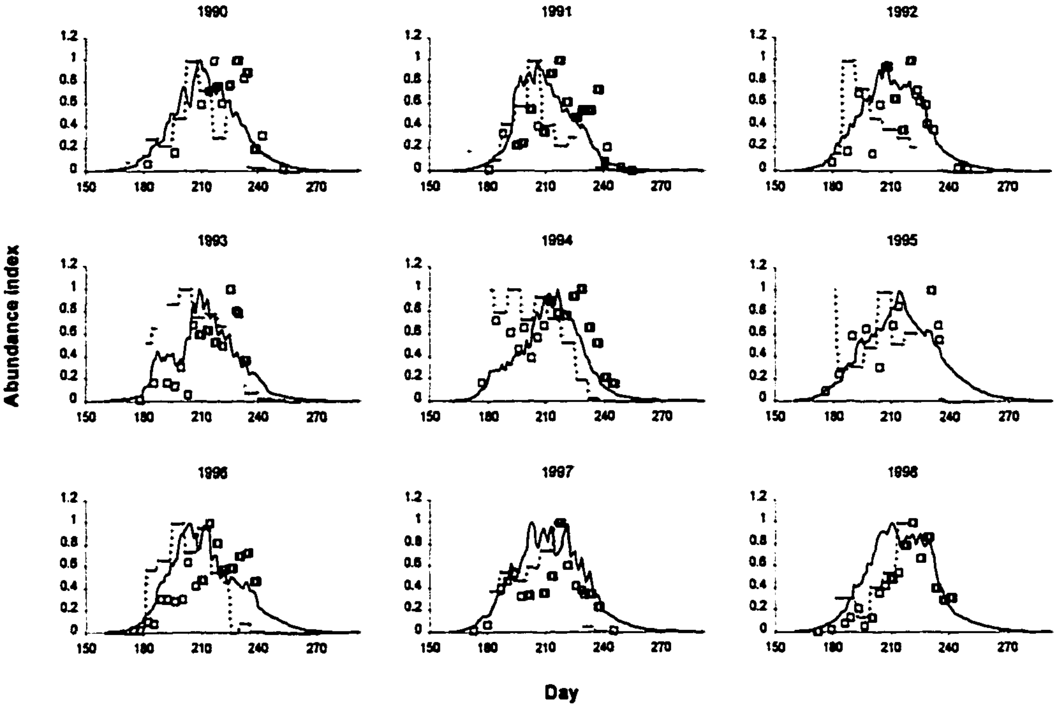


Fig. 3.10 Comparison of the daily abundance (lines), purse seine CPUE (squares) and 114 troll CPUE (dot lines) timing patterns for the Icy Strait/U. Chatham fishery, 1990-1998.

The daily abundance, purse seine and troll CPUE curves are obtained in the similar ways as in Fig. 3.9.

for each year, severe misallocations of catch might be reflected in extreme R/S values for some stocks over several years. The historical region-wide median R/S's is 1.82 (Table 3.10), which appears to be comparable to the 1963-1987 median (1.79) of R/S's for Prince William Sound pink salmon estimated by Geiger et al. (1996). Estimated median annual R/S's for the individual stocks are 0.7 to 1.2 times the regional median (in the range of 1.3 to 2.2) (Table 3.10). This limited range gives no indication of a severe misallocation of the harvests to any specific stock, and the most extreme values of annual ratios of R/S's (>2.0 or <0.5) observed show no systematic patterns.

Table 3.10 Region-wide annual recruits per spawner (R/S) and the ratio of the annual stock R/S to the regional-wide annual R/S, 1979-1998

Year	Region-wide R/S	Ratio of the annual stock R/S to the regional-wide annual R/S								
		ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT
1979	1.54	0.5	0.7	0.9	1.2	0.9	1.1	1.8	1.9	1.0
1980	0.95	1.3	0.7	0.5	1.7	0.5	0.8	2.1	1.2	1.7
1981	0.91	1.3	2.2	0.8	0.7	1.0	0.5	0.8	0.9	1.2
1982	3.33	0.6	0.7	1.2	0.5	1.7	0.8	1.1	1.5	0.8
1983	1.76	0.7	1.6	0.6	1.0	1.4	1.0	0.9	1.0	1.0
1984	1.24	0.9	0.7	0.9	0.8	1.2	1.1	1.4	1.2	0.7
1985	3.60	0.9	0.7	0.9	0.5	0.5	0.9	2.1	1.8	0.6
1986	0.93	0.4	2.9	1.0	1.1	0.6	1.5	1.8	0.7	0.5
1987	0.76	0.4	0.7	1.0	0.6	1.8	0.4	1.1	1.9	1.4
1988	1.04	1.4	0.7	1.2	0.5	1.5	1.0	0.6	1.3	1.5
1989	2.17	0.7	2.2	1.4	1.2	1.1	0.9	1.0	1.2	0.3
1990	2.08	0.9	0.7	0.7	1.1	0.9	0.6	1.4	1.5	0.7
1991	2.61	0.3	2.0	0.6	0.5	1.1	0.8	1.3	1.3	0.7
1992	2.59	0.3	1.2	0.5	0.4	0.9	1.3	1.6	1.2	1.1
1993	2.15	0.8	0.8	1.2	0.8	2.5	0.9	1.2	1.1	0.2
1994	4.13	0.6	1.2	1.4	0.5	1.1	0.9	0.9	1.1	1.1
1995	1.20	1.2	0.9	1.0	0.6	0.3	1.8	0.9	0.8	1.6
1996	1.15	0.2	1.1	0.7	1.1	0.9	1.8	1.6	1.1	0.6
1997	2.67	0.7	1.5	1.1	0.6	2.0	0.5	1.2	1.4	0.8
1998	1.88	0.8	0.9	1.0	1.1	1.8	0.6	1.0	1.7	0.7
Max	4.4	1.4	2.9	1.4	1.7	2.5	1.8	2.1	1.9	1.7
Median	1.8	0.7	0.9	0.9	0.8	1.1	0.9	1.2	1.2	0.8
Min	0.8	0.2	0.7	0.5	0.4	0.3	0.4	0.6	0.7	0.2

Sensitivity analysis

Influences of migration proportion

In the reconstruction, we use the backward migration proportions as a mechanism to tune the migration behaviors of some stocks (see "Migration routes and proportions" section).

We examined the model's sensitivity to the change of these proportions. Here the I. Frederick/Seymour stock is used as an example for it is a stock traversing most of the fisheries in this area, so the influence of its migration proportions would be the highest.

We set the migration proportion (p_1) of the I. Frederick/Seymour stock in the O. Frederick fishery on day t+1 returning from the L. Chatham route on day t to 0.0, 0.3, 0.6 and 0.9, respectively. The results (Table 3.11) are straightforward: changes in the migration proportion of a stock simply change the stock compositions for the fisheries this stock traverses. An increase in p_1 means a decrease of the proportion (p_2) from the alternative W. Admiralty route, which decreases the percentage of this stock (IFS) in the fisheries along this route and increases the percentages of other stocks in the same fishery (Table 3.11).

Table 3.11 Influence of migration proportion of the I. Frederick/Seymour stock on the stock composition of the Icy Strait/U. Chatham fishery for 1998.

Stocks	Migration proportion (p_1)			
	0.0	0.3	0.6	0.9
STT	12.3%	13.7%	15.4%	17.7%
TEN+BAS+WAD	24.6%	27.8%	31.7%	36.7%
PER	11.9%	13.4%	15.2%	17.6%
OFR	10.9%	12.4%	14.4%	17.0%
IFS	36.4%	28.3%	18.2%	5.2%
ICY	3.9%	4.4%	5.0%	5.8%

The annual harvest rates of the individual stocks are not very sensitive to the change of migration proportion (Table 3.12). For the small changes observed, an increase of p_1 (and the resultant decrease in p_2) increases the harvest rates for other stocks in the fisheries along the W. Admiralty route because the same amount of effort is directed to other stocks. Similarly, an increase of p_1 decreases the harvest rates for the L. Chatham stock. The effects of p_1 on harvest rates of the three stocks (Frederick Sound and Stephens Passage) migrating through both routes are canceled out.

Table 3.12 Influence of migration proportion of the I. Frederick/Seymour stock on the stock-specific harvest rates for 1998.

Stock	Migration proportion (p_1)			
	0.0	0.3	0.6	0.9
Icy Strait/U.Chatham	7%	8%	9%	10%
Tenakee Inlet	36%	37%	37%	38%
Basket Bay	39%	39%	40%	40%
W.Admiralty	15%	16%	18%	20%
Peril Strait	56%	56%	57%	57%
L.Chatham	45%	42%	41%	39%
O.Fredeick	60%	60%	61%	61%
I.Frederick	55%	55%	55%	55%
Stephens/Taku	24%	23%	23%	24%
Total	45%	45%	45%	45%

Influence of migration speed

We also examine the model's sensitivity to the misspecification of migration speed. For this analysis, we halved the migration speed to 10 miles/day (referred as 10mi case) from 20 miles/day (20mi case), thus doubling the residence times in all fisheries.

Table 3.13 shows that the change in migration speed does not introduce too many changes to the average stock composition and harvest rates from 1977 to 1998 for the individual stocks. This is also true for the annual stock compositions and harvest rates (results not shown).

The change in speed does bring changes to the entry timing of each stock to their first fishery and the abundance timings of each stock in the fisheries it traverses. For example, the entry timing of the I. Frederick/Seymour stock into Icy Strait obtained from the 10mi-migration speed is ahead of that obtained from the 20mi-migration speed by 10 days at the 50% dates. This is because the escapement timing is not changed for both cases, but the overall residence time increases 10 days for the 10mi case compared to the 20mi case. The total entry of all the stocks to the Icy Strait/U. Chatham fishery in the 10mi case is only 5 days ahead of the 20mi case at the 50% date of the cumulative timing curves. This is close to the average increase in the residence times for all the stocks that pass this fishery.

Table 3.13 Average stock composition and average stock-specific harvest rates, 1977-1998, for two migration speed cases.

"20mi" is for the case of the 20 miles/day, and "10mi" for the case of 10 miles/day.

Quantity	Speed	Stock									
		ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT	Total
Composit.	20mi	10.4%	11.6%	5.3%	4.2%	7.4%	11.0%	10.5%	30.3%	9.2%	100.0%
	10mi	10.6%	11.4%	5.4%	4.3%	7.6%	10.4%	12.4%	29.2%	8.7%	100.0%
Harv. Rate	20mi	11.5%	37.8%	28.8%	15.3%	38.6%	26.8%	38.7%	40.2%	20.1%	33.4%
	10mi	12.5%	37.2%	30.3%	16.4%	39.8%	24.4%	44.4%	38.6%	17.3%	33.4%

Discussion

As judged from the validation, the historical reconstructions of pink salmon stocks in the NSE inside area are reasonable. This reconstruction work provides stock-specific run size (numbers of recruits) data that can be used for stock recruitment analysis. The reconstructed inseason abundance data can be used as the input for management policy studies (Chapter 4) and used for fishery planning.

The reconstruction model we applied is deterministic. The correctness of the results is based on the plausibility of the model assumptions. The biggest and most uncertain assumptions we made are for the migratory behavior of the pink salmon stocks in this region. Tagging studies have demonstrated that there are large annual variations in the migration routes for some stocks, such as O. Frederick and I. Frederick/Seymour stocks. We based these assumptions on historical tagging studies and some general beliefs of the managers. Sensitivity analyses were performed to examine the response of reconstruction to using alternative assumptions about the migration routes. The influence of the migration proportion on stock compositions in a fishery that a stock traverses can be large. But the model has some flexibility to allow us to tune the proportion parameters and partially change the migration behavior for some stocks. Although we have simplified migrations in some areas and used only one set of migration proportion parameters for all years, our validation and sensitivity analyses imply that the results provide at least a coarse approximation of the stock specific patterns.

The specification of migration speed might be another source of modeling error. Migration speed of salmon is observed to be different among years for a stock, among different stocks for a year, as well as declining in the season for a stock (Mundy et al. 1993). This kind of data is not available for pink salmon in the NSE inside waters. The use of 20 miles/day for the migration speed seems reasonable from the fit of abundance timing curves to those of purse seine CPUE and 114 troll CPUE data. Slower speeds produce abundance timings that were slightly earlier than those obtained from the speed as we used.

There are two kinds of run reconstruction methods published in the literature. One is the boxcar method as described in Starr and Hilborn (1988) and used elsewhere (Mundy 1993; Cave and Gazey 1994). Templin et al. (1996) suggested a migration model using a Markov chain mechanism. Their model has several merits as stated by Templin et al. (1996). Yet some research still needs to be done to determine the backward migration matrices used in this kind of model. An attempt to use inverse forward migration matrices in a similar run reconstruction model produced lots of large negative abundance values. Although the latter model is mathematically correct, we found it to be unusable for our run reconstruction. Nevertheless, the forward Markov chain migration model was useful for our management simulations (Chapter 4).

Data quality might be the major limitation for this run reconstruction. Of the three kinds of input data used in the run reconstructions, migration data are the most limited, escapement data are sparse, but catch data are fairly reliable. To improve the run reconstruction work, more tagging studies would be useful, specifically to determine the migration proportions for the Frederick Sound and Seymour Canal stocks. More accurate migration speed data or residence time data are also important.

Escapement data need to be improved in two aspects. Total escapement estimates are limited (Van Alen 2000). The peak escapement counts used in this chapter might underestimate the true escapement (Jones et al. 1998). The use of the multiplier 2.5 to convert the peak escapement counts to the total escapement is somewhat ad hoc, although these estimation methods are being revised (Ben Van Alen, pers. comm.).

Escapement timing information is limited for most streams. In the application of the Bayesian hierarchical model (Chapter 1), we found that the timings of the stocks in adjacent streams are very similar (Fig. 3.3). This implies that quality timing information for several representative streams for a stock area might suffice for that stock. In Chapter 2 we found that one or more postpeak counts are needed to improve the escapement and escapement timing estimation.

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Chapter 4. Optimal inseason management of pink salmon given uncertain run sizes and seasonal changes in economic value

Abstract

In this study, we developed a stochastic simulation model that simulates the inseason abundance dynamics of pink salmon stocks, the fleet dynamics and management of purse seine fisheries in the north Southeast Alaska inside waters. Uncertainties in annual stock size and run timing, fleet dynamics and both preseason and inseason forecasts were accounted for explicitly in this simulation. The simulation model was applied to evaluating four kinds of management strategies with different fishing opening schedules and decision rules. The ranking of the management strategies is apparently determined by the evaluation criteria applied. When only flesh quality is concerned, both the current and a more aggressive strategy, as long as they adapted themselves to the run strength, were able to provide higher quality fish without compromising the escapement objectives. When the value of the eggs is also a concern, the management strategies that have more intensive late opening schedules might be preferable. When both flesh quality and the value of eggs are considered, the ranking of the management strategies depends on the timing of the stocks.

Introduction

Pink salmon in Alaska is primarily managed to achieve adequate and well-distributed escapement for all stocks (Van Alen 2000). The Alaska constitution mandates that renewable resources "shall be utilized, developed and maintained on the sustained yield principle." Flesh quality of this species is another major issue for the managers and the salmon industry. Record salmon harvests in Alaska combined with increasing supplies of farmed salmon have reduced the value of salmon in general (Knapp 1992). The market for pink salmon has been particularly affected, in part because of record supplies and in part because pink salmon is one of the least-preferred species. In recent years, processors have been unwilling to purchase all of the pink salmon that could have been caught, and in particular have declined to purchase fish with low flesh quality (Ben Van Alen , ADF&G, Juneau, Alaska pers. comm.).

The flesh quality and thus commercial value of pink salmon are greatly affected by where and when they are caught. Pink salmon migrate to their spawning grounds from the open ocean, often passing through several fishing districts on their way to their natal stream (Chapter 3). As these salmon approach their spawning grounds, their flesh becomes paler as pigment is transferred from muscle to skin tissue and softer as muscle tissue is converted to energy and self-maintenance mechanisms cease to function. Thus, the value of salmon increases the farther offshore they are harvested. Similarly, later-running fish tend to head more directly for their stream of origin, and are in a riper condition when they first enter the fishery. Thus, quality and commercial value are maximized by harvesting earlier in the season, and in offshore districts farthest from the spawning grounds.

However, to ensure conservation the opposite strategies are optimal. The strength of the run varies greatly from year to year in a mostly unpredictable manner (Hofmeister 1994). Thus, it is much safer to start harvesting fish late in the season, when the necessary escapements are already on the spawning grounds. Also, different stocks can sustain different harvest rates. In the offshore districts fish of different origins are mixed

(McKinstry 1993), and a harvest rate appropriate for one stock may overharvest a weaker one. For conservation purposes, it is safer to harvest stocks nearer to their spawning grounds, where they are less mixed and stock-specific harvest rates can be applied.

This study aims at finding the balance point of these two conflicting objectives and identifying management strategies that might potentially increase the economic value of the pink salmon fisheries yet not compromise the conservation goals.

We use simulation techniques to evaluate these management strategies. Simulation (or preseason planning) models are often used to examine alternative harvesting strategies to achieve specific management objectives (Walters and Buckingham 1975; Starr and Hilborn 1988; Zheng 1988; Cave and Gazey 1994; Link and Peterman 1998). Our simulation models use run size and timing information as well as migration information (obtained from run reconstruction techniques in Chapter 3) to evaluate catch and escapement management goals under alternative harvest regimes.

In this study, we build a stochastic simulation system that simulates the fleet dynamics of the purse seine fishery, the inseason abundance dynamics and management of pink salmon. Uncertainties in stock size, run timing, fleet dynamics, and both preseason and inseason forecasts are considered in this simulation. The simulation model is applied to evaluate four management strategies with contrasting fishing opening schedules and management objectives.

Models and methods

Simulation studies

This model simulates the migration of the pink salmon stocks, the interactions between pink salmon stocks and the fishing fleet, and the inseason management process that regulates fishing effort in the inside waters of northern Southeast Alaska (NSE). This is a complex stochastic simulation system. We build the uncertainties in stock size, run timing and fleet dynamics into the model. Only one fishing season is simulated; thus, long-term effects of the management strategies are not considered. Preseason and inseason forecast errors are considered using the approximation in the "Preseason prediction and inseason forecast errors" section below.

The simulations are conducted as follows:

(1) Generate the set of daily entry abundance of all stocks to their respective entrance fisheries by drawing randomly from the sets of historically reconstructed daily entry data obtained from Chapter 3.

(2) Calculate stock-specific daily abundance $N_{s,d,t}$, of stock s, fishery d on day t by the inseason abundance dynamics model.

(3) Generate fishery openings based on the management strategy applied and the status of the pink salmon stocks (see "Management strategies" section below).

(4) Predict the daily number of boats $B_{d,t}$ for fishery d for each opening by the daily abundance $N_{d,t}$ using Eq. 4.7 below.

(5) Predict daily harvest rate $h_{d,t}$ by the number of boats $B_{d,t}$ for each opening using Eq. 4.8 below.

(6) Calculate daily catch $C_{s,d,t}$ by fishery and stock. Calculate the value of catch $VC_{s,d,t}$ (Eq. 4.10 below), and the number of females $FC_{s,d,t}$ in the catch (Eq. 4.13 below).

(7) Calculate daily escapements $E_{s,t}$ for each stock. Calculate the number of females $FE_{s,t}$ in the escapement (Eq. 4.14 below). Calculate cumulative escapements.

(8) *Repeat* steps 1-8 from $t = T_1$, the day the first fish enters NSE until t=T_2, the day the last fish escapes the fisheries.

(9) Calculate entire-season summary statistics for each stock, including total run size, escapement, whether escapement was above 80% of the goal, date of 50% escapement, proportion of females in the escapement (Eq. 4.16 below), total catch, average value of the catch (Eq. 4.11 below), and proportion of females in the catch (Eq. 4.15 below).

(10) *Repeat* steps 1-9 5,000 times for each management strategy. Calculate the average values of the summary statistics across the 5000 simulation runs.

(11) Analyse the simulation results for each management strategy based on the evaluation criteria (see "Evaluation criteria for the management strategies" section below).

Details of the component models of this simulation are given below.

Inseason abundance dynamics

Models of salmon migration are described and used by several authors for multi-time-period reconstructions in a backward way, and for preseason planning or simulation in a forward way (Royce et al. 1963; Paulik and Greenough 1966; Starr and Hilborn 1988; Cave and Gazey 1994). Starr and Hilborn (1988) described a preseason-planning model using their boxcar type reconstruction framework but running in a forward way. We apply a similar boxcar forward migration model in our simulation. The equations involved are listed below using similar notation to that used in the run reconstruction model in Chapter 3:

$$(4.1)\quad N_{s,b,d,t} = N^{*}_{s,b-1,d',t-1}$$

$$(4.2)\quad N_{s,1,d,t} = x_{s,t,d}$$

$$(4.3)\quad C_{s,b,d,t} = h_{d,t} N_{s,b,d,t}$$

$$(4.4)\quad N^{*}_{s,b,d,t} = N_{s,b,d,t} - C_{s,b,d,t}$$

$$(4.5)\quad E_{s,t+1} = N^{*}_{s,B_s,D_s,T_s}$$

$$(4.6)\quad C_{s,d,t} = \sum_{\{b \text{ of } s \text{ in } d \text{ at } t\}} C_{s,b,d,t}$$

where $C_{s,b,d,t}$, $N_{s,b,d,t}$ and $N^{\bullet}_{s,b,d,t}$ denote the catch, abundance before catch and abundance after catch for block *b* of stock *s* in fishery *d* on day *t*, respectively. The $N^{\bullet}{}_{s,B_s,D_s,T_s}$ is the abundance after catch before the block escaping the last fishery (at its last time period T_s in its last fishery D_s). The quantity B_s is the total residence time of stock *s*. The $h_{d,t}$ is the harvest rate for fishery *d* on day *t*, which is predicted by the fleet dynamics models (see "Fleet dynamics" section below). The $E_{s,t}$ is the escapement for stock *s* on day *t*. The $x_{s,t,d}$ is the daily entry of stock *s* to an entrance fishery *d* from the Gulf of Alaska. For example, the O. Frederick stock enters two entrance fisheries from the Gulf of Alaska: Icy Strait /U. Chatham and L. Chatham Strait. The $C_{s,d,t}$ is the total catch of all blocks of stock *s* in fishery *d* on day *t*.

Data sources

The data needed for the simulation are stock size and timing data, migration and harvest rate information and sex ratio data.

The simulated daily harvest rates for each opening are based on the number of boats operating. The simulated number of boats is modeled as a function of the daily abundance for that opening (see "Fleet dynamics" section below). We use the historical data for the number of boats by opening obtained from ADF&G's Integrated Database (Van Alen 2000), and the daily abundance and harvest rate data obtained from the run reconstruction of Chapter 3 to estimate the two relationships (see "Fleet dynamics" section below).

Stock size and daily entry data for each stock are obtained from the historical run reconstructions of Chapter 3. Migration data are the same as those used in Chapter 3. Sex ratio data are also obtained from the ADF&G Integrated Database.

Fleet dynamics

In Southeast Alaska (SEAK), the management of purse seine fisheries is mostly based on the abundance of pink salmon. Purse seiners harvest most of the pink salmon caught in NSE (over the period 1980-1998, the seine fleet averaged 95.0% of the total catch). In NSE, purse seine fishing is allowed in all districts except Lynn Canal and the Stephens Passage/Taku River area, where drift gillnet fisheries are operated to harvest sockeye salmon as well as pink and summer chum salmon. The Icy Strait troll fishery targets and catches a relatively small amount (1980-1998 average 4.0% of the total catch) of pink salmon in June. For the sake of simplicity, only the purse seine fleet is modeled in this analysis.

Purse seine fisheries throughout SEAK are opened concurrently, which has the effect of spreading the fishing effort more evenly over the entire region (Van Alen 2000). The maximum number of boats operating in each season is limited by the number of entry permits (about 420). The number of boats operating generally varies over the course of the season, peaking in the middle, possibly in response to changes in pink salmon abundance. However, the Hidden Falls terminal hatchery fishery for summer chum attracts a large proportion of purse seiners early in the season. As the season progresses, most of purse seiners move to the southern SEAK waters to harvest later running pink salmon.

The number of boats fishing in the inside waters of NSE (except at Hidden Falls) is generally a small fraction of the total fleet and varies considerably within the season. We analyse the distribution of seining boats versus the salmon abundance, and that of harvest rates versus the number of boats based on the reconstructed data from Chapter 3. We then use these relationships to predict the number of boats and the harvest rates for each scheduled opening in the simulation.

Several authors have observed that the number of fishing boats attracted to a fishing area is positively related to the abundance of salmon (Hilborn 1985; Link and Peterman 1998). We examined this kind of relationship for the pink salmon fisheries in the NSE inside waters (see Fig. 4.1 for an example) following Link and Peterman (1998). A nonlinear function with lognormal error:

$$(4.7) \quad B_{d,t} = \alpha N_{d,t}^{\beta} e^{\varepsilon}$$

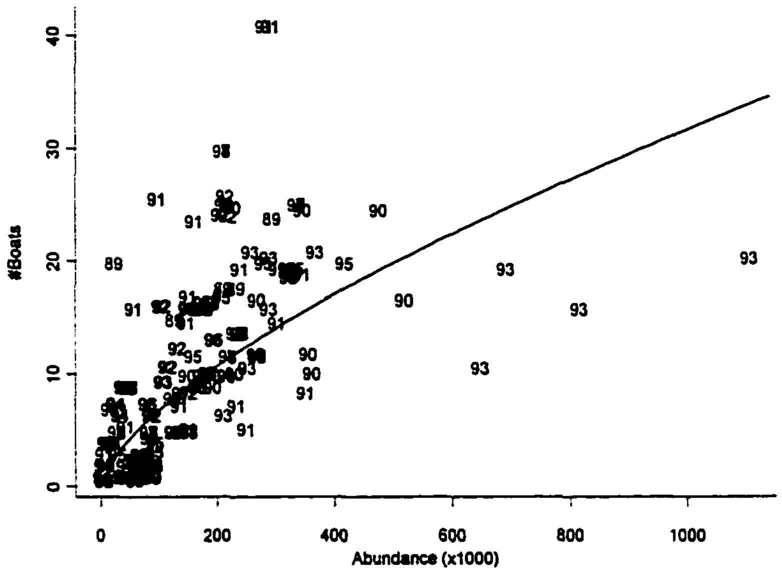

Fig. 4.1 The number of boats versus pink salmon abundance (×1000) for the O. Frederick fishery, 1989-1998, and the fitted curve (line). Data from other fisheries have similar patterns.

is fit to the number of boats data (from ADF&G Integrated Database) and daily salmon abundance data, 1989-1998 (data before 1989 are sparse), from Chapter 3. Here $\varepsilon \sim N(0,\sigma^2)$ is the model error term. By taking logarithms of Eq. 4.7, we obtained a linear regression model with $\ln(B_{d,t})$ as the dependent variable and $\ln(N_{d,t})$ as the independent variable. The linear regression results are shown in Table 4.1. These results are used in the simulation to predict the daily number of boats for each opening from the daily abundance of a fishery.

Table 4.1 Regression statistics from the model fits of the number of boats and abundance (×1000) data, 1989-1998.

Fishery	α	β	σ	R^2
Icy Strait/U. Chatham	0.298	0.547	0.811	0.26
Basket Bay [a]	0.052	0.953	1.071	0.35
Tenakee	0.304	0.853	1.247	0.36
W. Admiralty	0.464	0.396	1.003	0.11
L. Chatham	0.010	1.259	0.670	0.55
O. Frederick	0.298	0.676	0.781	0.45
I. Frederick	0.740	0.589	0.870	0.42

Note:

[a] Excluding the number of boats of Hidden Falls hatchery chum fishery which targets on summer hatchery chum salmon

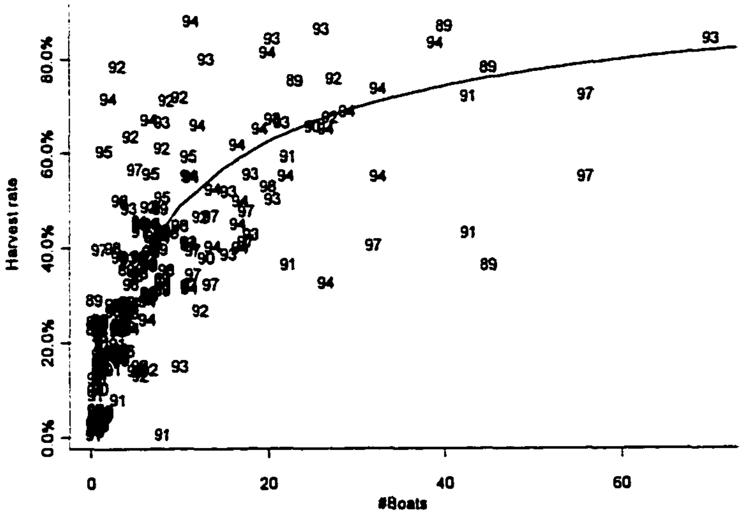

Fig. 4.2 The harvest rate versus the number of boats for the Basket Bay fishery, 1989-1998, and the fitted curve (line, transformed to the original scale from Eq. 4.8). Data from other fisheries have similar patterns.

Link and Peterman (1998) fitted a similar function as Eq. 4.7 to the data of harvest rates and the number of boats. We find that a linear model of logit-transformed harvest rates versus the number of boats yields better fit and residual distributions for our data (Fig. 4.2). So a linear regression model

$$(4.8) \quad \text{logit}(h_{d,t}) = a + b\ln(B_{d,t}) + \varepsilon$$

is fit to the data of harvest rates obtained from Chapter 3 and the number of boats for each fishery from 1989 to 1998. Here $\text{logit}(h_{d,t}) = \ln(h_{d,t}/(1-h_{d,t}))$ and $\varepsilon \sim N(0,\sigma^2)$ is the model error term. The results are shown in Table 4.2.

Table 4.2 Regression statistics for the relationship of harvest rate versus the number of boats.

Fishery	a	b	σ	R^2
Icy Strait/U. Chatham	-4.896	0.894	0.747	0.56
Basket Bay [a]	-1.877	0.798	0.855	0.60
Tenakee	-1.524	0.753	0.846	0.63
W. Admiralty	-3.568	1.087	0.943	0.60
L. Chatham	-3.582	1.031	0.661	0.70
O. Frederick	-4.428	1.514	1.649	0.44
I. Frederick	-3.026	1.112	1.070	0.59

Note:

[a] Excluding the number of boats of Hidden Falls hatchery chum fishery which targets on summer hatchery chum salmon

Inseason management

While the limited entry program controls the capacity of the purse seine fleet, area and time openings and closures are used within a season to regulate the amount and distribution of purse seine fishing effort in SEAK (Van Alen 2000). Specific open areas and fishing periods are established by emergency order based on the strength of the pink salmon returns (ADF&G 2001). The run strength is first estimated by preseason forecasts and further monitored during the season on a weekly basis through spawning escapement information obtained from aerial surveys and pink salmon CPUE data (ADF&G 2001).

The objectives of the fishery management in this region are to achieve escapement goals that are well distributed to all stocks as well as to promote a harvest of good quality fish in excess of spawning escapement needs. To maintain the quality of the harvests, managers implement an adaptive management procedure (ADF&G 2001). For areas where strong returns are expected, an aggressive fishing schedule early in the season is implemented; otherwise for weak running areas, total season closures or late openings are implemented for conservation purposes. For the strong running fisheries, a 2-day-on/2-day-off fishing schedule is applied during the peak of the season to avoid overwhelming the capacity of the processing sector when large numbers of fish present (ADF&G, 2001). The baseline management strategy in the simulation simulates this kind of management practice in SEAK.

Preseason prediction and inseason forecast errors

In the simulation, the initial opening schedule of each fishery is based on the forecast run strength (classified as strong or weak, see the following section) of the local stocks. Yet, large variability in run strength is observed for salmon stocks because of the influence of both physical and anthropogenic factors (Adkison et al. 1997). Early in the season, managers don't know the true abundance of returns of the stocks and initially base their estimates of the run strength on preseason predictions (Van Alen 2000). These preseason predictions for run strength have a large amount of error (Quinn and Marshall 1989). So managers collect further information (e.g. escapement and CPUE data) over the fishing season to improve the abundance estimates (Zheng and Mathisen 1998).

Including the detailed processes of preseason prediction and inseason forecasts in a simulation would be beyond the scope of this study. But we approximate the preseason prediction errors and inseason forecast uncertainties in our simulation through the following steps. We assumed a lognormal error distribution for the simulated run size of pink salmon stocks:

$$(4.9) \quad \ln(\hat{R}_s) = \ln(R_s) + \varepsilon$$

where R_s is the actual run size for stock s, and ε is the model error term with $\varepsilon \sim N(0,\sigma^2)$. We set the standard deviation of the residuals σ to 0.7 (from the Ricker model fit, only the density-dependent effect is considered) (Quinn and Deriso 1999, p. 107). So the coefficient of variation (CV) of the pre-season forecast $\hat{R}_s$ is about 70% (Quinn and Deriso 1999, p. 102), a relatively large prediction error.

The present inseason forecasting techniques based on sex ratio, catch and effort data enable managers to typically obtain relatively accurate inseason forecasts for the total run of NSE by the end of the third week of the fishing season (Zheng and Mathisen 1998). In our simulation we assume that the managers manage based on the preseason forecast for the first three weeks. We assume they know the run strength exactly on the fourth week of the season for each fishery. Then the run strength of the fisheries are reassessed and opening schedules are rearranged.

Management strategies

(i) Baseline:

This management strategy approximates what is actually implemented by the management agency in this region (ADF&G 2001). Based on the historical opening patterns of NSE inside fisheries, we designed an opening schedule for each fishery for this management strategy (Table 4.3).

This management strategy is an adaptive one because it considers the run strength of the local stocks (Table 4.3) of a fishery. If the run strength of the local stocks is strong, an intensive opening schedule will be arranged for this fishery, and vice versa.

Specifically, the decisions made for the fishing opening schedules of a fishery are based on the preseason forecasts (Eq. 4.9) of the run strength of its local stocks for the first three weeks of the fishing season. Then the managers are assumed to know the run strength exactly on the fourth week, and opening schedules are rearranged based on the true run strength for the rest of the fishing season.

The (forecast or true) run strength of a local stock is classified as strong if its run size is above the historical average run size (Table 3.8); if below, the run strength is classified as weak. Different fishing periods and opening schedules are arranged for these two classes (Table 4.3). If all of the local stocks of a fishery are strong, intensive opening schedules are arranged to increase the fishing effort for these stocks; otherwise, less intensive openings are arranged to reduce the fishing pressure on these stocks.

Table 4.3 Fishing opening schedule used for the baseline management strategy for strong- or weak-running local stocks.

Fishing period from day_1 to day_2 is denoted as "day_1~day_2" and a "x_1-day-on/x_2-day-off" fishing schedule is denoted as "x_1-x_2".

Fishery	Local stocks	Fishing period and schedule	
		For strong runs	For weak runs
Icy Strait/U. Chatham	ICY, STT	6/28~7/23: 1-3; 7/24~9/1: 2-2	6/28~9/1: 1-5
Basket Bay	BAS, PER	6/23~7/18: 1-3; 7/19~9/1: 2-2	6/23~8/27: 1-5
Tenakee Inlet	TEN	6/23~8/7: 1-3	6/23~8/7: 1-5
W. Admiralty	WAD	7/28~9/1: 2-2	7/18~9/1: 1-5
L. Chatham	LCH	7/18~9/1: 2-2	7/18~9/1: 2-2
O. Frederick	OFR	7/23~9/1: 2-2	7/23~9/1: 1-3
I. Frederick	IFS	7/3~8/12: 1-3	7/3~8/12: 1-6

(ii) Aggressive schedules: adaptive or non-adaptive

The purposes of these management strategies are to examine the influence of a more intensive opening schedule for the stocks and the role of the adaptive procedure.

First, an adaptive aggressive strategy similar to the baseline is designed. Compared to the baseline strategy, it involved a shift in effort to more intensive early-season openings for strong runs in the entrance areas of Icy Strait and Chatham Strait (North of Pt. Gardner) (see stocks bolded in Table 4.4). The length of the fishing periods of the latter fisheries on these strong stocks are reduced to make the total number of days the stocks are targeted comparable to that of the baseline strategy. The scheduled openings for other fisheries are the same as those used in the baseline policy. The opening schedules for weak runs are also the same as those used in the baseline strategy (Table 4.3).

Table 4.4 Fishing schedule used for all fisheries under the non-adaptive aggressive management strategy or for strong runs under the adaptive aggressive management strategy.
The notation is the same as in Table 4.3.

Fishery	*Fishing period and schedule*
Icy Strait/U. Chatham	**6/28~8/7: 3-1**
Basket Bay	**6/23~8/7: 3-1**
Tenakee Inlet	6/23~8/7: 1-3
W. Admiralty	**6/28~8/7: 3-1**
L. Chatham	7/18~9/1: 2-2
O. Frederick	7/23~9/1: 2-2
I. Frederick	7/3~8/7: 1-3

For the non-adaptive aggressive strategy, intensive fishing schedules (Table 4.4) are implemented for all the fisheries regardless of the run strength of the local stocks. This will increase the fishing effort and thus the risk to the escapement of the weak runs greatly.

(iii) Conservative schedule:

A non-adaptive fishing schedule is designed as the conservative strategy (Table 4.5). A specific fishery will be opened 10 days after the middle date of its fishing season (Table 4.5) regardless of the run strength of the local stocks. This management strategy is intended to ensure enough escapement for each stock first, and then allow fishing late in the season.

Evaluation criteria for the management strategies

We evaluate each management strategy based on its average performance in meeting conservation goals, and on fish value objectives and other considerations. Sex ratio is examined to evaluate the proportion of females in catch and escapement. To examine the selective pressure of each management strategy on the stocks, we also calculate the average escapement timing and compare that with the escapement timing under the unexploited state of the stocks.

Table 4.5 Opening schedule for the conservative management strategy.

Fishery	Date of the middle season	Fishing period and schedule
Icy Strait/U. Chatham	7/28	8/7~9/1: 2-2
Basket Bay	7/28	8/7~9/1: 2-2
Tenakee Inlet	7/13	7/18~8/7: 1-3
W. Admiralty	8/12	8/20~9/6: 2-2
L. Chatham	8/12	8/20~9/6: 2-2
O. Frederick	8/12	8/20~9/6: 2-2
I. Frederick	7/23	8/2~8/17: 2-2

A stock-recruitment analysis is not done for these stocks, so optimum escapement is not known. We use the historical average value of the escapement (E*) for each stock between 1977 and 1998 (see Table 3.5) as its escapement goal. The frequency of failure to meet the escapement goal of a stock is used as a measure of conservation objectives, and is defined as the percent of simulation runs with escapement less than 80% of its historical average ($\%(E<0.8E^*)$).

Specific data on changes in flesh quality and the value of fish eggs over the course of the fishing season are not available to us, so we choose five value-index functions to represent the range of possibilities (Fig. 4.3, Table 4.6). Some are based only on the deterioration of flesh quality over time (Cases 1-3) (with different declining rates) while the others are based on the combined value of flesh quality and fish eggs (Cases 4 and 5) (the earlier in the season, the higher the flesh quality; the later in the season, the higher the roe value).

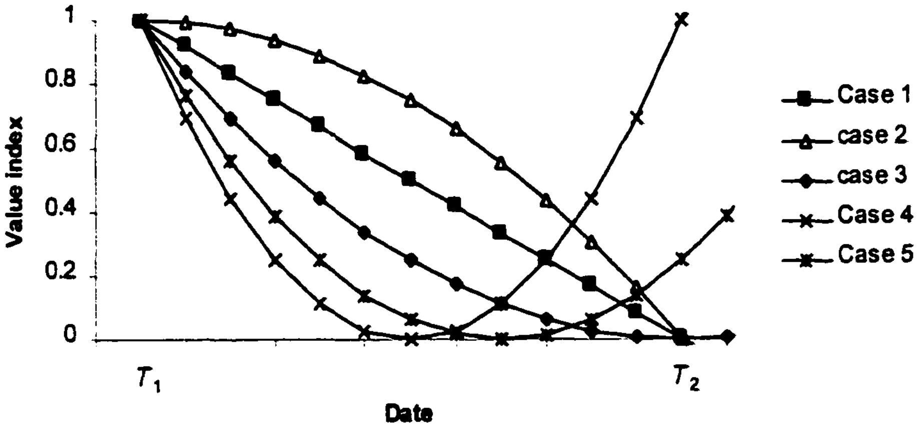

Fig. 4.3 Value-index curves of pink salmon

Based on these value-index functions, the value of the catch is calculated by

(4.10) $VC_{s,d,t} = C_{s,d,t} \times V_t$

where V_t denotes a fish value index at time t. The average value of the annual catch of each stock is

(4.11) $AV_s = \sum_{d,t} VC_{s,d,t} \Big/ \sum_{d,t} C_{s,d,t}$

Table 4.6 The properties of value-index functions for pink salmon. The T_1 and T_2 are defined in "Simulation studies" section.

Case	V_t	V_{T_1}	$T_{V_t=0}$	V_{T_2}	a	b	c
1	a+bt	1	T_2	0	$T_1/(T_2-T_1)$	$-(T_2-T_1)^{-1}$	-
2	At^2+bt+c	1	T_2	0	$-(T_2-T_1)^{-2}$	$-2aT_1$	$1-aT_1^2-bT_1$
3		1	T_2	0	$(T_{V_t=0}-T_1)^{-2}$	$-2aT_{V_t=0}$	$1-aT_1^2-bT_1$
4		1	$(T_1+T_2)/2$	1			
5		1	$T_1+(3/4)(T_2-T_1)$	≈0.5			

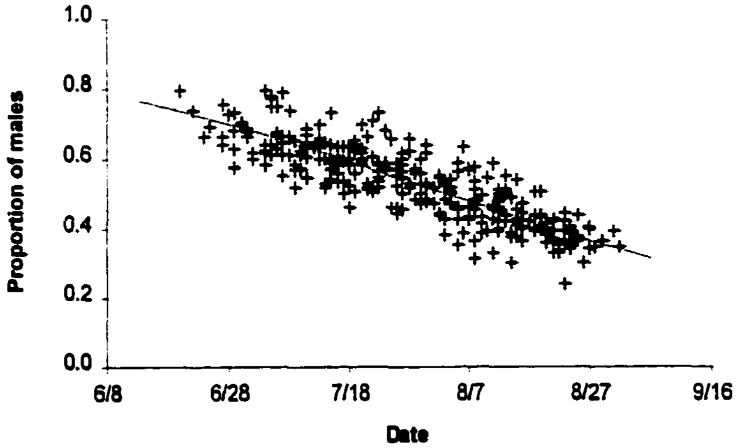

Fig. 4.4 Proportion of males in the samples obtained from the sex ratio surveys conducted by ADF&G in the inside waters of NSE, 1984-1997, and the fitted curve (line, transformed to the original scale from Eq. 4.12).

Sex ratio changes over the course of the season (males usually return earlier than females) (Fig. 4.4), and this could also be used as an indicator of quality changes in fish flesh. At the same time, the number of spawning females is thought to be the primary determinant of the reproductive potential of each salmon stock. For example, Mathisen

(1962) found that male sockeye salmon could fertilize the eggs of many females; it is thus thought that a female- biased escapement might be preferable to a male-biased one.

We model the proportion of males in the catch as a function of date using the following procedure. The logits of the proportion of males are regressed against time using a generalized linear model:

$$(4.12)\quad \mathrm{logit}(M_t) = a + bt + \varepsilon$$

where M_t is the proportion of males in the catch. We use data for the proportions of males for the entire NSE inside waters for model fitting (Fig. 4.4). The estimate for a is 4.974 and for b is -0.0230. The predicted value of logit(M_t) $(= \hat{a} + \hat{b}t)$ is used to calculate the predicted proportion of males in the catch $\hat{M}_t (= \exp(\hat{a} + \hat{b}t)/(1 + \exp(\hat{a} + \hat{b}t)))$ in the simulation. The number of females in the catch is calculated by

$$(4.13)\quad FC_{s,d,t} = C_{s,d,t}(1 - \hat{M}_t)$$

and the number of females in the escapement is calculated by

$$(4.14)\quad FE_{s,t} = E_{s,t}(1 - \hat{M}_t)$$

the proportions of females in the stock-specific annual catch and escapement are calculated by:

$$(4.15)\quad FC_s = \sum_{d,t} FC_{s,d,t} \Big/ \sum_{d,t} C_{s,d,t}$$

and

(4.16) $FE_s = \sum_t FE_{s,t} \Big/ \sum_t E_{s,t}$

respectively.

Selective exploitation of some segments of the run caused by different management strategies could affect stream entry timing of the spawners, which in turn might decrease the fitness and production of salmon populations (Alexandersdottir 1987). McNeil (1969) found that the delay time of arrival of pink salmon into Sashin Creek was correlated to the decrease in fry survival that period.

We examine the selective pressure caused by different management strategies for each stock by comparing the average of the dates of 50% escapement over the simulation runs with the date of 50% escapement under the unexploited state of the stock.

Model verification and validation

We did a verification test of the simulation model. The purpose of this test is to check that forward simulations using the abundances of fish entering NSE and fishery-specific harvest rates estimated in run reconstruction reproduced abundance and harvest rate estimates and the escapement data used in run reconstruction.

In this test, we use the set of daily harvest rates by fishery and daily entry abundances by stock obtained from the run reconstruction in Chapter 3 as the inputs for the simulation model. We run the simulation model for each year separately from 1977 to 1998. For each year, each simulation test quantity is averaged across the simulation runs. Then the annual averages of each test quantity are further averaged across years to obtain an overall average. Finally, the overall average is compared with the true average values from the run reconstructions by a percent difference quantity (bias): (average – true average)/true average.

The baseline schedule is also compared with the run reconstruction results to ensure that the behavior of our simulation model was in qualitative agreement with real world observations.

Results

Model verification and validation

For the raw entry data, the simulation model completely recovers the "true" reconstruction results for all the years tested, for all stocks except the Stephens/Taku stock (Table 4.7). For this latter stock, the backward proportion (0.85) of the escapement on day $t+1$ coming from Icy Strait/U. Chatham on day t (see Fig. 3.2) can not be converted to a constant forward proportion of fish in Icy Strait/U. Chatham on day t migrating to the escapement area on day $t+1$. An approximate value of 0.6 is used in the simulation.

Table 4.7 Percent differences between the average stock-specific harvest rates or frequency of escapement failure (%(E<0.8E*)) obtained from the verification test (using raw entry data) and the run reconstructions, 1977-1998.

The abbreviations are the same as in Table 3.1. We use the same kind of abbreviations for these stocks in the following tables and figures.

	Stock									
Quantity	ICY	TEN	BAS	WAD	PER	LCH	OFR	IFS	STT	Mean
Harvest rate	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%
%(E<0.8E*)	0%	0%	0%	0%	0%	0%	0%	0%	25%	3%

Fig. 4.5 shows that if the entry data are smoothed (e.g., by a 5-day moving average method), the boxcar model underestimates the run reconstruction results (the results from the verification test using the raw entry data are equivalent to the run reconstruction results).

Primary tests that include some stochastic components, such as the fleet dynamics component, show that their results always underestimate those from the run reconstructions, but are more comparable to the results from the verification test with smoothed data. Therefore, we compare our baseline schedule with the verification test using the smoothed data.

Fig. 4.5 also compares the baseline schedule with the verification test. The baseline approximately matches the verification test with smoothed entry data, indicating that the simulation models are able to simulate the actual fishery and inseason management processes. Therefore, we proceed to conduct the formal simulations for the four management strategies in the following section.

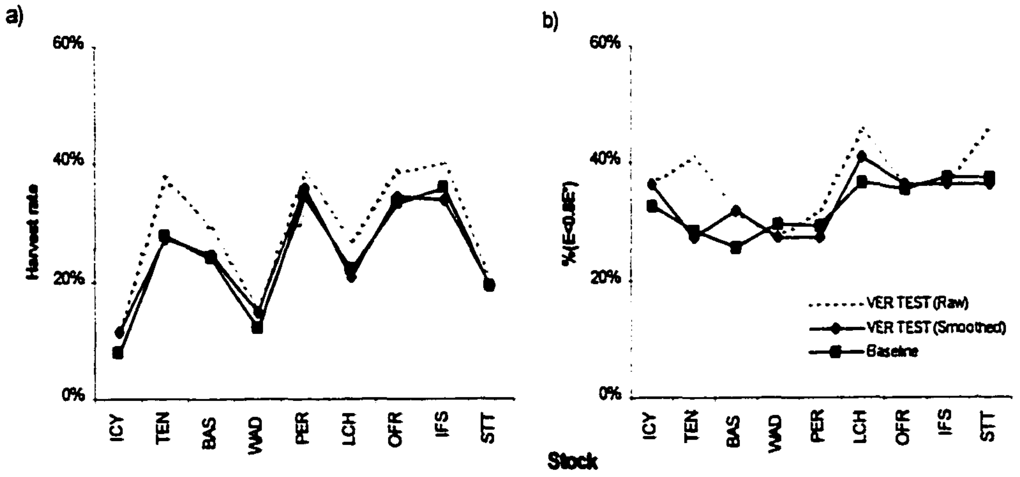

Fig. 4.5 Comparison of (*a*) average stock-specific harvest rates or (*b*) frequency of escapement failure (%(E<0.8E*)) between the verification test (VER TEST) for the raw and smoothed daily entry data and the baseline schedule.

Management strategies

Average catch value

Fig. 4.6 illustrates the average catch value of each stock evaluated for five value-index functions and four management strategies.

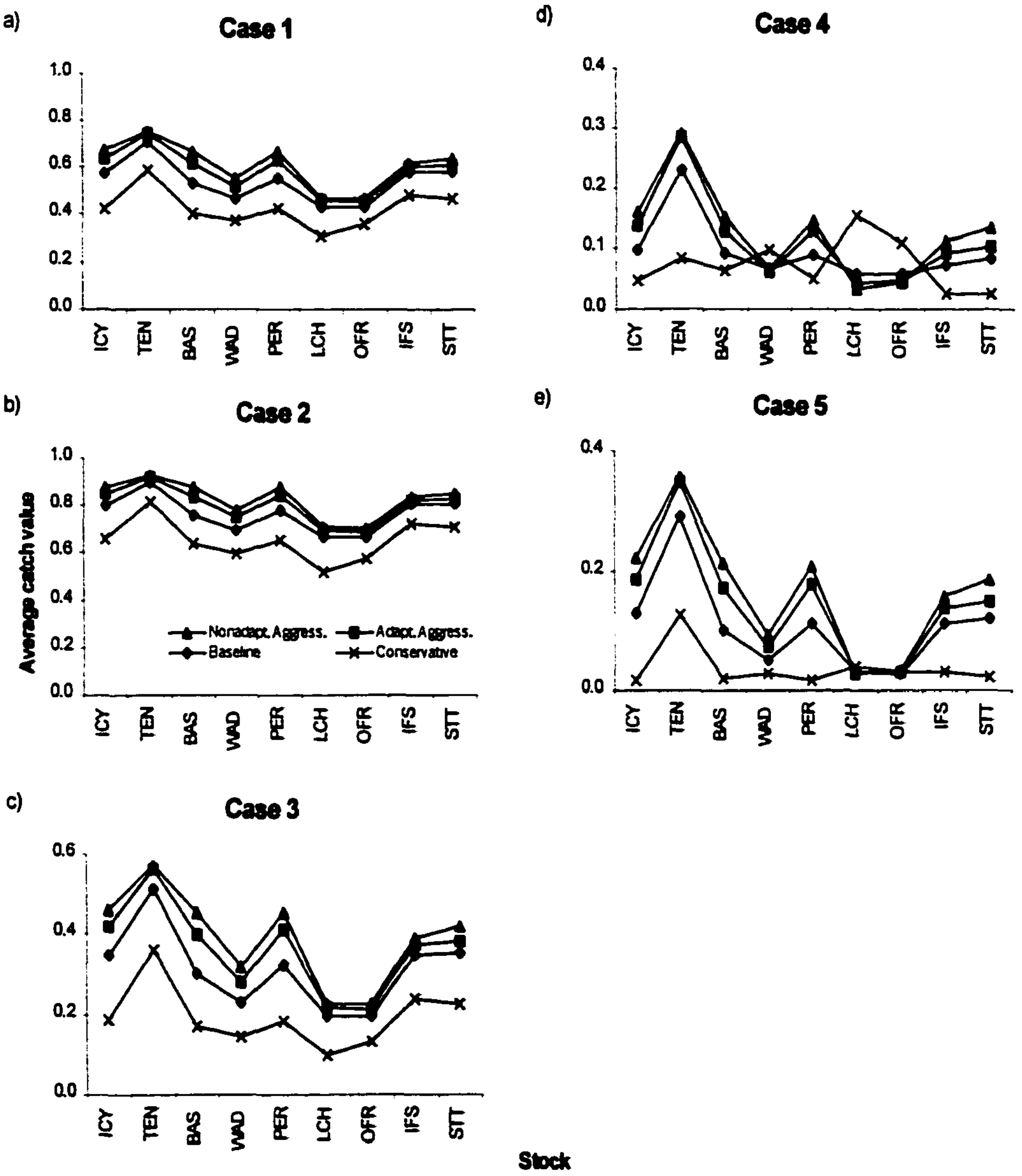

Fig. 4.6 Average catch value of each stock for five value-index functions and four management strategies.

The ranking of the management strategies based on the fish value criterion is the same for Cases 1-3 (where only flesh quality is considered) (Fig. 4.6*a-c*): the non-adaptive aggressive strategy results in catch with the highest value, then the adaptive aggressive and baseline strategies; the conservative strategy results in catch with the poorest value.

When both flesh quality and the value of eggs are considered (Cases 4 and 5), the ranking of the management strategy is affected by the run timing of the stocks (Fig. 4.6*d-e*). The ranking is the same to Cases 1-3 for the early timed stocks for both Cases 4 and 5. For the three latest-running stocks (W. Admiralty, L. Chatham and O. Frederick), the value of the catch taken in the conservative strategy and even in the baseline strategy might exceed that from other management strategies depending on the relative weights put on the value of eggs late in the season. For example, for the L. Chatham and O. Frederick stocks in Case 4 (a U-shaped curve, more weights put on the value of eggs late in the season), fish taken in the conservative strategy have much higher value than those from other strategies (Fig. 4.6*d*); the value is about the same for Case 5 (less weights put on the value of eggs late in the season) for all management strategies (Fig. 4.6*e*).

Proportions of females in catch and escapement

The two aggressive opening schedules reduce the proportion of females in the catch (Fig. 4.7*a*). In contrast, the conservative scenario results in a high proportion of females in the catch (Fig. 4.7*a*). The baseline scenario yields results in between.

Only minor differences in the proportions of females in the escapement are observed for each stock under different management strategies (Fig. 4.7*b*). The proportions of females in the escapement are the highest for the two aggressive strategies, then the baseline and conservation strategies. This is in an opposite order to the proportions of females in the catch.

The differences in the stock-specific harvest value, and the proportions of females in the stock-specific annual catch and escapement for each scenario are due to the variation in run timing for different stocks. The catch of the earliest-running stock, the

Tenakee Inlet (TEN) stock, has the highest value, the lowest proportions of females in the catch and escapement, respectively (Figs. 4.6-4.7), whereas the latest running stocks, O. Frederick (OFR) and L. Chatham (LCH) stocks, have catch with the poorest value (except the conservative strategy in Case 4 and 5), and highest proportions of females in the catch and escapement for all management strategies, respectively.

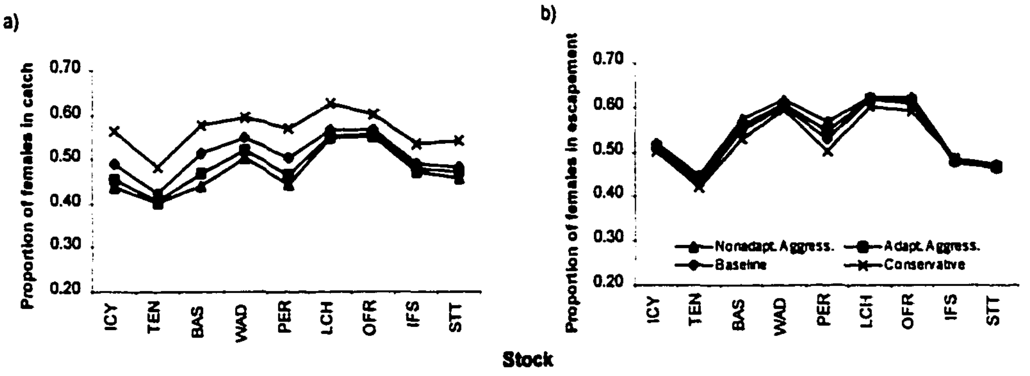

Fig. 4.7 Proportion of females in (*a*) annual catch or (*b*) annual escapement for each stock obtained from four management strategies.

Frequency of escapement failure and the role of the adaptive procedure

The aggressive management strategy that is adaptive to the run strength yields comparable results (harvest rate and frequency of escapement failure) to those of the baseline strategy (Fig. 4.8), although the average catch composition (fish value and proportion of females) differs between the two management strategies.

Without the adaptive procedure, the aggressive management strategy increases the harvest rates for the weak runs of the stocks greatly compared to the adaptive case (Fig.4.8*a*), thus increasing the frequency of escapement failure of the stocks (Fig.4.8*b*).

For the conservative strategy, the stock-specific harvest rates (Fig.4.8*a*) are low and more fish are allowed to spawn. So the frequency of escapement failure caused by this strategy is the least (Fig.4.8*b*).

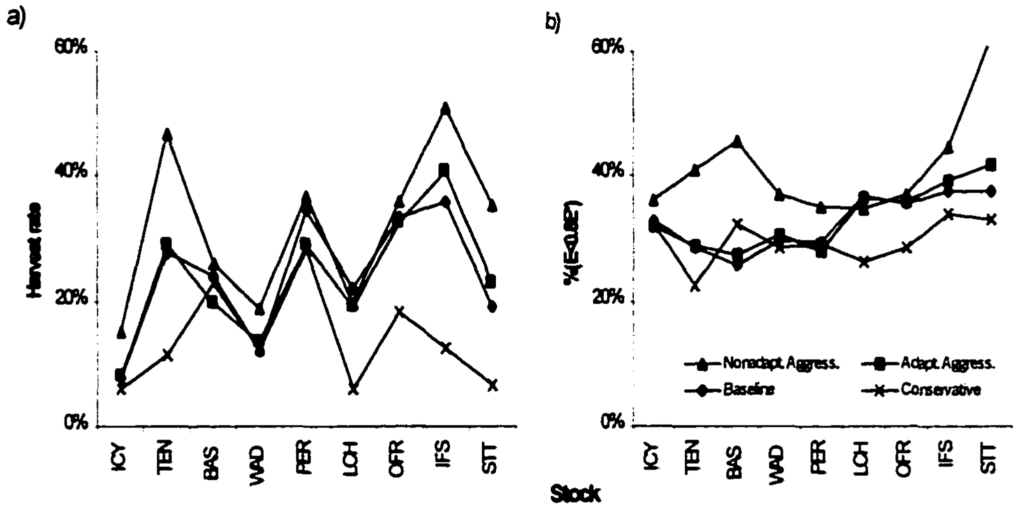

Fig. 4.8 (*a*) Harvest rates and (*b*) frequency of escapement failure (%(E<0.8E*).

Escapement timing

The two aggressive management strategies, which have more intensive early opening schedules, result in escapement timing that is later than the escapement timing under the unexploited state for all stocks except the I. Frederick/Seymour and Stephens/Taku stocks (Fig. 4.9). In contrast, the conservative strategy results in escapement timing that is earlier than the escapement timing under the unexploited state (Fig. 4.9). The baseline strategy results in escapement timing comparable to that under the unexploited state.

The escapement timing of the I. Frederick/Seymour stock is un-sensitive to the opening schedules, possibly because of the relatively un-intensive effort of the I.

Frederick fishery (Tables 4.3-4.5) and its large annual escapement. The Stephens/Taku stock has complex migration behavior (see "Migration of pink salmon stocks" section in Chapter 3). The changes in the opening schedules of the Icy Strait/U. Chatham fishery might not have direct impact on the escapement timing of the Stephens/Taku stock.

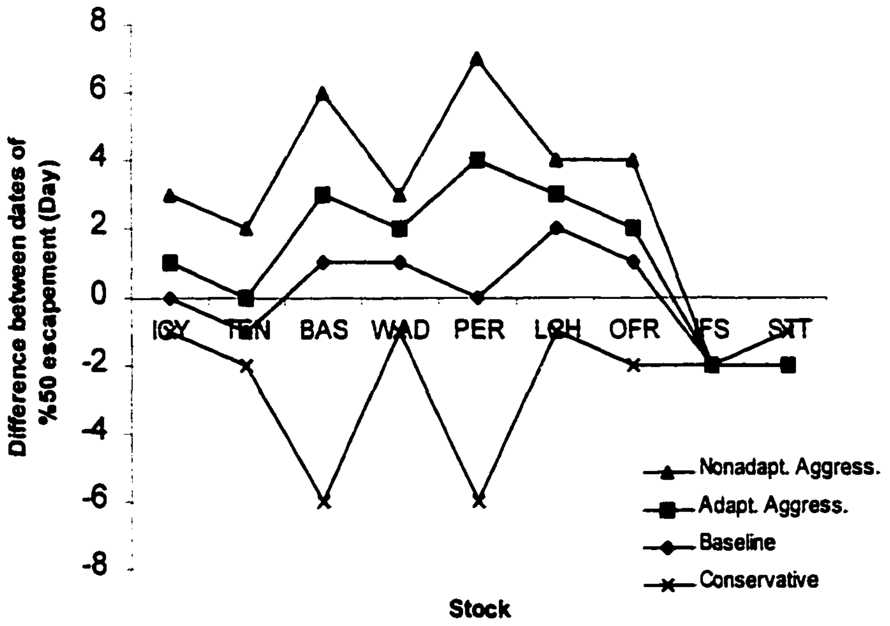

Fig. 4.9 Differences of dates of 50% escapement between exploited and unexploited states for each stock with four management strategies.

Discussion

In this chapter, we build a simulation system that simulates the complex inseason fish abundance dynamics, the seine fishery and fishery management. We apply this simulation model to evaluate four contrasting management strategies with different opening schedules and decision rules.

The ranking of the management strategies is apparently determined by the evaluation criteria applied. When only flesh quality is concerned, both the adaptive aggressive and the baseline management strategy, which is also adaptive to the run strength, are able to provide fish with high value (flesh quality) as well as reduce the catch of females in the returns without compromising the escapement goals. An aggressive management strategy without adaptation to the run strength of the local stocks results in a high frequency of escapement failure for weak runs. The conservative management strategy is sub-optimal in that it might results in harvesting fish of poorer value.

The increasing emphasis on getting ripe eggs instead of flesh might change quality considerations. In contrast to salmon flesh, eggs increase in value over the course of the run. When the value of the eggs is a concern, the management strategies that have more intensive late opening schedules might be preferable. When both flesh quality and the value of eggs are considered, the ranking of the management strategies depends on the timing of the stocks.

Another conservation concern besides the escapement abundance goals is the effect of selective pressure of fishing on the fitness and production of the stocks. Management strategies that emphasize certain segments of the total run might deplete some component stocks of those segments partially or entirely. In the former case (partial depletion), the escapement timing of the stocks might also be affected. In our simulation, the aggressive (or conservative) strategy might cause selective exploitation of the early (or late) segments of the runs. The results show that the aggressive strategies cause the escapement to occur later than the unexploited state, and the conservative strategy results in escapement that occurs earlier for most stocks. As escapement timing may be driven by localized selective pressures (Alexandersdottir 1987), such a shift in escapement timing might decrease the fitness and productivity of the stocks in the long term.

Our simulation conclusions are based on a single species management simulation for pink salmon, the primary target species of the purse seine fishery in NSE inside waters. Management constraints for reducing by-catch of other salmon species might affect these conclusions. For example, the Hawk Inlet Shore fishery management must consider the conservation of sockeye salmon. This fishery must be closed in July after 15,000 sockeye salmon have been harvested (ADF&G 2001). Wild summer chum salmon also pose a management problem for W. Admiralty and O. Frederick fisheries where they are relatively abundant. The Hidden Falls summer chum terminal hatchery fishery also affects the fleet dynamics models in our simulations, although our models were based on data that already incorporated this effect. Including the complicated structure of these populations and their effects on the purse seine fleet was beyond the scope of this study. Nonetheless, the validation tests we conducted show that our simulation models are complex enough to simulate the actual fishery and management system reasonably well. Further refinements of this model are possible.

Our simulations were also limited in considering only a single season. The alternative management strategies potentially differ in their long-term performance. Although we did not explicitly consider the long term, these effects are a function of escapement and the fraction of females in the escapement, which we did monitor.

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