

# Climate change and salmon production in the Northeast Pacific Ocean

S.R. Hare and R.C. Francis

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**Abstract:** Alaskan salmon stocks have exhibited enormous fluctuations in production during the 20th century. In this paper, we investigate our hypothesis that large-scale salmon-production variability is driven by climatic processes in the Northeast Pacific Ocean. Using a time-series analytical technique known as intervention analysis, we demonstrate that Alaskan salmonids alternate between high and low production regimes. The transition from a high(low) regime to a low(high) regime is called an intervention. To test for interventions, we first fitted the salmon time series to univariate autoregressive integrated moving average (ARIMA) models. On the basis of tentatively identified climatic regime shifts, potential interventions were then identified and incorporated into the models, and the resulting fit was compared with the non-intervention models. A highly significant positive step intervention in the late 1970s and a significant negative step intervention in the late 1940s were identified in the four major Alaska salmon stocks analyzed. We review the evidence for synchronous climatic regime shifts in the late 1940s and late 1970s that coincide with the shifts in salmon production. Potential mechanisms linking North Pacific climatic processes to salmon production are identified.

## Introduction

In the mid-1970s, ocean conditions in the North Pacific Ocean underwent a dramatic and abrupt change (Graham 1994). Coincident with the physical regime shift, Alaskan salmonids entered an era of greatly increased production that has persisted into the 1990s (Fig. 1). Throughout their long (over 100 yr) commercial exploitation history, several of the Alaskan salmon species have demonstrated "red noise" variability, wherein periods of high (low) production tend to persist for a lengthy period before abruptly reversing to the opposite state. For example, in the 1930s and early 1940s, salmon landings were high, followed by an era of low catches from the late 1940s to late 1970s. As Alaskan landings increased in the late 1970s, several North American west coast stocks, notably Oregon coho salmon (*Oncorhynchus kisutch*; Percy 1992), went into a prolonged period of decline.

Much early research on variability in salmon survival (and therefore production and catch) focused on the freshwater stage of their life cycle, attempting to link survival to conditions in their spawning and rearing habitat. The period spent at sea was regarded as relatively unimportant. There is now a growing awareness of the importance of the marine environment in determining salmon production (e.g. Percy 1984; Beamish and McFarlane 1989).

Variability in marine survival of salmon is poorly understood (Mathews 1984). Numerous studies have attempted to correlate survival with environmental factors, though few have proven useful in predicting salmon abundance or assisting in management decision making (Percy 1992). Part of the difficulty in elucidating the driving factors of survival is that the relationship between the environment and survival is clouded by many factors. Biotic (e.g. intra- and inter-specific competition, prey availability, predation) and abiotic (environmental variables, habitat) factors not only exhibit complex relationships with survival (non-linear, threshold) but are themselves often highly correlated.

Despite these drawbacks, the importance of attempting to understand the causes of variable survival should not be underestimated (Francis and Sibley 1991). In particular, understanding large-scale and long-term variability would benefit both fishery managers and fishermen (Shepherd et al. 1984).

Large marine ecosystems fluctuate in response to physical forcings that occur over a number of time intervals. There appears to be a nested hierarchy of interacting processes occurring on different time scales that are relevant to their dynamics, ranging from relatively discrete processes that occur over times on the order of 1 yr or less (e.g., the 1970 North Pacific winter atmospheric circulation pattern (Hollowed and Wooster 1992)), to processes that persist over long time periods and fluctuate at the inter-century level (Baumgartner et al. 1992). What we are most interested in identifying in this analysis are regimes that define points in time, separated by intervals on the order of decades, where major jumps or shifts in the level of abundance occur in large marine ecosystems. Therefore, in examining the interannual dynamics of various biological components of large marine ecosystems, what we see are responses to these nested hierarchies of interacting processes occurring at different time scales and working synergistically to create pattern. In this analysis, it is pattern at the regime level that we are trying to interpret.

We hypothesize that regional variability in salmon production is driven by large-scale climate change, reflected in North Pacific atmospheric-oceanic regime shifts. Under this hypothesis, salmon populations exhibit two characteristics: relatively stable production while a particular regime persists, followed by a rapid transition to a new production level in response to the physical regime shift. If large-scale salmon production is closely related to North Pacific climate processes, we should find coherent shifts in mean production levels across both species and area.

In addition to the late 1970s regime shift, we surmise that an earlier shift, opposite in character, occurred in the late 1940s. Based on evidence summarized in the Discussion, we tentatively identify the regime shifts as taking place in the winters of 1946-47 and 1976-77. Our hypothesis suggests that two shifts in Alaskan salmon production should be detectable: a decrease in the late 1940s and an increase in the late 1970s.

To test this hypothesis, we proceed by statistically analyzing the historical production dynamics of four major Alaskan salmon stocks: western and central sockeye salmon (*Oncorhynchus nerka*), southeast and central pink salmon (*Oncorhynchus gorbuscha*). While many researchers have noted the aforementioned swings in production (e.g., Beamish and Bouillon 1994), there remained the possibility that the changes might be either random processes or nonsignificant, in a statistical sense. Owing to the high serial correlation (lack of independence between successive observations), the *t*-test for equality of

means cannot be used to test for production shifts. We utilize a time-series technique known as intervention analysis to identify the significance, magnitude, and form of structural shifts (interventions) in the four time series. We identify and test the timing of the interventions by matching the onset of the physical regimes with the life history of the different species of salmon. Intervention analysis is a relatively recent statistical technique recommended as a method for detecting and quantifying non-random change in an unreplicated experiment (Carpenter 1990).

To test for interventions, we fitted univariate time-series models of the Box-Jenkins (1976) autoregressive integrated moving average (ARIMA) class. These ARIMA models provide a baseline fit to the correlation structure exhibited by the time series. Interventions are subsequently identified by analyzing model residuals. Model parameters are re-estimated incorporating the intervention(s), and the models compared on the basis of several criteria. After identifying the timing and nature of the interventions, we then review the evidence for synchronous large-scale physical regime shifts in the North Pacific.

### **Time-Series Modeling and Intervention Analysis**

The use of time-series analysis to model fish population dynamics has increased in recent years. Most of the theoretical development and initial application has taken place in the econometric and business forecasting literature. Recognition of the potential applicability to ecological problems appears to have begun with Moran (1949).

There are five classes of commonly applied time-series models (Jenkins 1979). The simplest, and most widely known, comprise the so-called Box-Jenkins ARIMA univariate models. Simple ARIMA models utilize only the history of the time series to “explain” its observed variability. The second class comprises the transfer-function noise (TFN) models, which relate an output-series variability to both its own history and that of one or more explanatory variables. A third class, related to TFN models, comprises intervention models which incorporate the effects of unusual events, natural or human-made, to modify ARIMA models. The other two classes comprise multivariate models. Multivariate stochastic models permit feedback among several time series and are often referred to as vector ARIMA models. The final class includes explanatory variables giving a multiple input-multiple output mode and are sometimes referred to as multivariate transfer-function models.

In addition to these time-series models, there has been a parallel development of frequency-domain models, principally in the engineering literature. In the frequency-domain models, processes are modeled as combinations of cosine waves. While theoretically translatable to time-domain models, there have been few applications in ecology. More recently, state-space models have generated a great deal of attention. In state-space, or more generally, structural modeling, a time series is decomposed into linear, seasonal, and irregular components (Harvey 1989). The central feature of structural models is the use of the Kalman filter (Kalman 1960; Kalman and Bucy 1961) for parameter estimation and forecasting. The principal difference between traditional time-series and structural models is the manner in which the error component is modeled. Though neither method has emerged as clearly superior, structural models are likely to receive increased attention.

The first published use of time-series modeling in the fisheries literature was Dunn and Murphy (1976) and Murphy and Dunn (1977), who used univariate and transfer-function models to forecast fish catch in an Arkansas reservoir. Univariate and/or transfer-function models have been used to model the population dynamics of American lobster (*Homarus americanus*; Boudreault et al. 1977, Fogarty 1988a, Campbell et al. 1991), rock lobster (*Jasus edwardsii*; Saila et al. 1980), skipjack tuna (*Katsuwonus pelamis*; Mendelsohn 1981), yellowtail flounder (*Limanda ferruginea*; Kirkley et al. 1982), menhaden (*Brevoortia patronus*; Jensen 1985), haddock (*Melanogrammus aeglefinus*; Pennington 1985), Alaskan salmon (Quinn and Marshall 1989; Noakes et al. 1987), winter flounder (*Pseudopleuronectes americanus*; Jeffries et al. 1989), blue whiting (*Micromesistius poutassou*; Calderon-Aguilera 1991), pilchard (*Sardina pilchardus*; Stergiou 1989), and striped bass (*Morone saxatilis*; Tsai and Chai 1992). Intervention analysis has been applied to Dungeness crab (*Cancer magister*; Noakes 1986), geoduck clams (*Panope abrupta*; Noakes and Campbell 1992), power plant impact on yellow perch (*Perca flavescens*) and alewife (*Alosa pseudoharengus*; Madenjian et al. 1986), and to forecast invertebrate yield (Fogarty 1988b). Vector ARIMA models have been applied to Great Lakes pelagic species (Cohen and Stone 1987;

Stone and Cohen 1990) and multivariate transfer-function models were used by Mendelsohn and Cury (1987, 1989) to explore catch per unit of effort in Ivory Coast pelagic fisheries.

In this paper, we use intervention models to determine if North Pacific regime shifts are reflected in Alaska salmonid time series. We provide a brief outline of the technique and explanation of time-series terminology and notation. Those seeking a more theoretical description should consult one of the numerous texts available including the seminal works on ARIMA model formulation (Box and Jenkins 1976) and intervention analysis (Box and Tiao 1975).

### Notation

ARIMA and intervention models have several different representations. We employ the following notation:

$$1) \quad \phi_p(B) \Phi_P(B^S) \nabla^d \nabla_s^D (Y_t^{(\lambda)}) = \theta_0 + \theta_q(B) \Theta_Q(B^S) a_t + \sum_{j=1}^k \frac{\omega_j(B) B^{b_j}}{\delta_j(B)} I_{jt}^T$$

$Y_t^{(\lambda)}$  is the discrete time series, which may be transformed to stabilize the variance using the Box-Cox (1964) power transformation. The most common transformations are square root ( $\lambda=0.5$ ), natural logarithm ( $\lambda=0.0$ ), and inverse ( $\lambda=-1.0$ ). No transformation is equivalent to a lambda value of 1.0. If required, a power transformation must be done as the first step in time-series modeling.

$\nabla^d$  is an “integrating factor” (the “I” in ARIMA), better defined as a differencing operation to induce stationarity in the mean of a series. The number of differences taken (which can be at various lags) is indicated by  $d$ . If required, differencing is the second step in ARIMA modeling.

$\nabla_s^D$  is a seasonal integrating factor(s) where  $s$  is the lag at which the  $D$ th seasonal difference is taken. While seasonal models are generally applied to weekly, monthly, quarterly, etc. data, they may also be applied to non-seasonal data that exhibit seasonal (i.e., periodic) behavior.

$\theta_0$  plays different roles depending on the value of  $d$  (order of differencing). For  $d = 0$ ,  $\theta_0$  is equal to the estimated mean of the transformed input series multiplied by the sum of the autoregressive components and moved to the right-hand side of the equality. For  $d \geq 1$ ,  $\theta_0$  is called the deterministic trend and is often omitted unless clearly called for (Wei 1990, p. 72).

$a_t$  is a random error component assumed to be normally independently distributed with mean 0 and constant variance  $\sigma_a^2$ .

$B$  is the backshift operator. By convention it is a special notation used to simplify the representation of lagged values:  $By_t = y_{t-1}$ ,  $B^s y_t = y_{t-s}$ . Note also the following definition:  $\nabla = 1 - B$ , thus differencing is often represented by:  $\nabla y_t = (1 - B)y_t$ .

$\phi_p(B)$  is the autoregressive polynomial of the form  $(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)$ . The term “autoregressive” is in reference to how the value of  $y$  is being regressed on its own past values plus a random shock, thus relating the present value of a process to a linear combination of its past values. An autoregressive process can be written as  $y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + a_t$ . An autoregressive process of order  $p$  is abbreviated AR( $p$ ), and lower orders than  $p$  need not be non-zero.

$\Phi_P(B^S)$  is the multiplicative seasonal autoregressive polynomial of the same form as the non-seasonal polynomial. Multiple seasonal autoregressive components may be included in the model, each of seasonality  $S$ . The subscript  $P$  identifies the presence of a seasonal component, and all coefficients other than that of the seasonal lag are set equal to 0.

$\theta_q(B)$  is the moving average polynomial of the form  $(1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)$ . The moving average term models the persistence of random effects over time and can be written as  $y_t = a_t$

- $+ \theta_1 a_{t-1} + \theta_2 a_{t-2} + \dots + \theta_p a_{t-p}$ . A moving average process of order  $q$  is abbreviated MA( $q$ ), and lower orders than  $q$  need not be non-zero.
- $\Theta_Q(B^S)$  is the multiplicative seasonal moving average polynomial of the same form as the non-seasonal polynomial. Multiple seasonal moving average components may be included in the model, each of seasonality  $S$ . The subscript  $Q$  identifies the presence of a seasonal component, and all coefficients other than that of the seasonal lag are set equal to 0.
- $I_{jt}^T$  represents the  $j$ th intervention and is analogous to a dummy variable in regression. Interventions can be either step ( $I = 1$  for  $t \geq T$ ,  $I = 0$  otherwise) or pulse ( $I = 1$  for  $t = T$ ,  $I = 0$  otherwise) functions. A step intervention indicates a permanent shift in the mean of a series, while a pulse indicates a one-time shock. There are several different system responses to step and impulse interventions, such as an abrupt permanent step, a step decay, and impulse decay.
- $\omega_j(B)$  is a polynomial of the form  $(\omega_0 - \omega_1 B - \omega_2 B^2 - \dots - \omega_s B^s)$  representing the initial impact of the intervention.
- $\delta_j(B)$  is a polynomial of the form  $(1 - \delta_1 B - \delta_2 B^2 - \dots - \delta_r B^r)$  representing the long-term impact of the intervention.
- $B^{b_j}$  models the delay in response associated with a particular intervention.

Nonseasonal ARIMA models use the notation  $(p, d, q)$  to compactly represent autoregressive, difference, and moving average orders. Seasonal models are expressed as  $(p, d, q) \times (P, D, Q)_S$ , with each seasonal component separately represented. Thus, a  $(1, 0, 5)$  model indicates the presence of additive lag 1 AR and lag 5 MA terms with smaller lag MA terms possibly present. A  $(1, 0, 0) \times (0, 0, 1)_5$  model also has lag 1 AR and lag 5 MA terms, but the parameters are multiplicative rather than additive.

### Model development

Univariate time-series model building, in the methodology of Box and Jenkins (1976), proceeds in the following fashion:

- 1) Model Identification. In this step, tentative models are identified. Determination of the need for power transformation (for variance stabilization) and differencing (to render the series stationary in the mean) are first evaluated. Plots of the autocorrelation and partial autocorrelation functions (ACF and PACF respectively) of the possibly transformed series are examined to assist in determining the order of the AR and MA components (Box and Jenkins 1976). Several other identification tools are also available, such as the extended sample autocorrelation function (ESACF; Tsay and Tiao 1984), generalized partial autocorrelation coefficient (GPAC; Woodward and Gray 1981) and the prediction variance horizon (PVH; Parzen 1981).
- 2) Parameter estimation. Following selection of a potential model(s), estimates of the parameters are calculated. Access to time-series software is almost essential as ARIMA model parameters must be fitted using a nonlinear estimation routine (though the models themselves are usually linear). Maximum likelihood procedures, usually based on the Cholesky decomposition or the Kalman filter, have been developed as an alternative to the early methods of least squares and approximate likelihood utilized by Box and Jenkins (1976). Standard errors are also computed, and parameters judged to not be significantly different from zero can be dropped. The remaining parameters are then re-estimated.
- 3) Model diagnostic checking. With a tentative model selected and parameters estimated, the adequacy of the model must be assessed to determine if model assumptions are met. One basic assumption is that the residuals  $a_t$  form a white-noise series. A common test is the portmanteau test of Box and Pierce (1970), which uses the residual ACF to test the joint null hypothesis that all serial correlations are equal to zero. It is also common in time-series analysis that several models may be adequate in the sense that the model residuals are reduced to white noise. Several model selection criteria have been developed to assist in model selection. In this analysis, we compared competing models using five criteria: mean absolute error (MAE), which measures the average one-step-ahead prediction error; the unbiased residual variance  $\sigma_a^2$ , equal to the residual sum of squares divided by degrees of

freedom; the coefficient of determination  $r^2$ , which is the amount of variance “explained” by the model; Akaike’s Information Criterion (AIC; Akaike 1974); and Schwarz’s Bayesian Criterion (SBC; Schwarz 1978). The AIC and SBC are performance statistics that balance statistical fit with model parsimony. The SBC utilizes a larger penalty function than the AIC, thus often suggesting a model with fewer parameters. Formulas for the model diagnostic and selection criteria are contained in the appendix.

### **Intervention detection and estimation**

In intervention analysis, the correlation structure is initially assumed to be unaffected by the interventions that are modeled as deterministic functions of time. Once the best ARIMA model has been selected, the three-step modeling sequence is repeated to identify and test the significance of interventions.

The original intervention methodology developed by Box and Tiao (1975) permitted estimation of intervention effects when the timing of the interventions was known a priori. To handle the situation where the number and timing of potential interventions are unknown, Chang and Tiao (1983) proposed an iterative detection technique using a likelihood ratio test. Interventions are identified in a stepwise fashion beginning with the residuals from the univariate model. Following detection and estimation of an intervention, model parameters are estimated and the resultant intervention model compared with the univariate model using the criteria cited above. The new model residuals can then be re-analyzed for evidence of other interventions.

A good general review of intervention models is contained in Wei (1990), while Noakes (1986) discusses the applicability of intervention analysis to fisheries problems.

There are two types of interventions, pulse and step. The first represents a discrete system shock; the second a permanent change in the mean level of a process. In this analysis, we model step interventions that result in permanent shifts in the mean level of salmon production. Step interventions can be modeled as abrupt (i.e., a one time-step jump) or delayed (e.g., ramp, impulse decay) processes. It should be noted that testing for different types of interventions increases the probability of identifying a spurious intervention. However, our use of the AIC and SBC performance statistics should minimize this risk. Two software packages, AUTOBOX (Automatic Forecasting Systems, Inc. 1992), and SPSS Trends (SPSS, Inc. 1993), were used for all analyses.

### **Data**

The salmon landings data used in this study were principally taken from an Alaska Department of Fish and Game (ADFG 1991) annual report. Data for 1992 were taken from Pacific Fishing (1994). We selected the four major regional groups of stocks: western Alaska sockeye salmon, central Alaska sockeye and pink salmon, and southeast Alaska pink salmon. Landings data for these regional stocks are more likely to reflect actual production than other Alaskan salmon stocks, as they have been the most intensively exploited stocks because of their high abundances and value. These four regional stocks accounted for over 80% of total Alaskan salmon catches (by number) for the period 1925-1992. To more accurately reflect salmon production by area (Fig. 2), we corrected the Alaskan landings for interceptions using data provided in Shepard et al. (1985), Harris (1989) and the Pacific Salmon Commission (1991). Details of the adjustments are provided in Francis and Hare (1994).

Catch data for these regional stocks are available from as early as the 1870s. We have restricted our analysis to 1925-1992 which we consider to be the period of full exploitation. If there is a “fishing up” effect in the early part of the record, the time-series analysis would be affected by this form of nonstationarity. Our time series span 68 years which is fully adequate for a proper time-series analysis (Newton 1988).

### **Results**

#### **Western Alaska Sockeye**

The western Alaska sockeye data required a square-root transformation to stabilize the variance. Differencing was not required. Examination of the ACF and PACF indicates rather complex dynamics in this time series, substantially different from the three other salmon time series (Fig. 3) Lags 1, 4, and 5 in the ACF and lags 1, 4, and 6 in the PACF were significant. A variety of models were fitted and

compared. Initial identification indicated three candidate univariate models: (6, 0, 0), (1, 0, 5), and the seasonal model (1, 0, 0) x (1, 0, 0)<sub>5</sub>. Diagnostics indicated residual serial correlation at lag 3 for the seasonal model, thus a moving average term was added and the resultant (1, 0, 0) x (1, 0, 0)<sub>5</sub> x (0, 0, 1)<sub>3</sub> model compared with the nonseasonal models. On the basis of the diagnostic statistics, the (6, 0, 0) model was judged to be the most parsimonious at representing the catch dynamics. Within this model, the lag 2, 3, and 4 autoregressive terms were statistically insignificant and, therefore, dropped from the final model. Residual analysis indicated that all serial correlation had been accounted for by the model. The final fitted model parameter estimates and standard errors for the univariate and subsequent intervention models are given in Table 1. Model diagnostics for the univariate and intervention models are given in Table 2.

Based on the physical regime shifts that we tentatively identify occurring in the winters of 1946-47 and 1976-77 (Francis and Hare 1994), we hypothesize that interventions in the western Alaska sockeye salmon time series should be detected around 1949-50 and 1979-80. Sockeye salmon from this region spend 1 or 2 years rearing in freshwater before migrating to sea where they are first exposed (and, probably, most vulnerable) to oceanic conditions. Bristol Bay sockeye salmon, which comprise most of the western Alaska sockeye salmon, generally spend two years at sea, thus the year classes that entered the ocean in 1977 would be caught in 1979.

We fitted two intervention models, the first incorporating a 1979 step, the second also incorporating a 1949 step. For the one-intervention model, the 1979 step was highly significant ( $p < 0.01$ ), and in the two-intervention model, both interventions were highly significant ( $p < 0.01$ ). In both cases, the best statistical fit was provided by simple step (i.e. no delay) interventions. Both models substantially outperformed the nonintervention model. The coefficient of determination,  $r^2$ , improved from 0.459 to 0.575 with the 1979 intervention and further increased to 0.623 with inclusion of the 1949 intervention (all model diagnostics reflect model fit in the transformed metric; thus for western Alaska sockeye salmon, the statistics result from model fitting in square root space). Both the AIC and SBC decreased substantially with the addition of each intervention.

The 2 intervention model differed slightly from the two other models in its ARIMA components. The lag 1 AR term, which had decreased in significance from the no intervention to the one-intervention model, dropped out of the model and a lag 3 AR term was added. The AR(5) coefficient was positive and highly significant in all three models, likely reflecting the pseudo-regular 5 year cycle (Eggers and Rogers 1987). The decrease in significance of the AR(1) term with incorporation of interventions was a feature of the model building sequence for each of the salmon time series. One explanation for this result is that a time series that alternates between different levels (or regimes) will have the statistical appearance of a low frequency series with high apparent autocorrelation. Removing the “regime effect” from the time series often accounts for most of the low frequency (i.e., lag 1) autocorrelation.

Resultant model fits and pre- and post-intervention means for the three models are illustrated in Fig. 4. For the one intervention (1979) model, estimates of the pre- and post-intervention means were 10.443 and 27.748 million respectively, resulting in an estimated step intervention of 17.305 million. In the two-intervention model, the 1949 step was estimated at -4.928 million and the 1979 step at 17.484 million. The three means were estimated at: 13.287 (1925-1948), 8.359 (1949-1978), and 25.843 million (1979-1992).

### Central Alaska Sockeye

The central Alaska sockeye salmon time series dynamics were much less complex than those of the western Alaska sockeye salmon. The ACF and PACF for the natural logarithm transformed series (Fig. 3) indicated either a (2, 0, 0) or a (1, 0, 1) model. Model diagnostics indicated a better fit for a (2, 0, 0) model. The univariate model fit was the best among the four salmon time series ( $r^2=0.644$ ). Model residuals showed no residual autocorrelation. Parameter estimates for the univariate and intervention models are given in Table 3, and model statistics in Table 4.

A large fraction of the central Alaska sockeye salmon (e.g., Kenai River, Chignik Lake runs) spend three years in the ocean before returning to spawn (Cross et al. 1983). In keeping with our hypothesis that the climate effect occurs during the first year of marine life, we tested for interventions in 1950 and 1980 for the central Alaska sockeye salmon time series. In the one-intervention (1980) model, the step intervention was highly significant ( $p < 0.01$ ) and led to an improvement in all diagnostic

statistics. The two-intervention model provided an equally large improvement as both interventions (1950, 1980) were highly significant. The lag 2 AR term, present in the no-intervention model, dropped out in each of the subsequent models. In addition, for reasons noted earlier, the magnitude of the AR 1 term also decreased with the incorporation of interventions.

The effective change in mean catch for the one intervention model (1980) was 6.937 million (Fig. 5). The estimated mean for the 1980-1992 period was 11.555 million, compared to an estimated mean of 4.618 million prior to the intervention effect. For the two-intervention model, the interventions were estimated to have decreased mean catch by 1.919 million (from 5.665 to 3.746million) between the 1925-1949 and 1950-1979 periods, and then increased mean catch by 8.086 million (to 11.832 million) for the 1980-1992 period.

### **Southeast Alaska Pink**

The southeast Alaska pink data required a natural logarithm transformation to stabilize the variance. The resultant ACF and PACF resembled central Alaska sockeye, indicating similar dynamics. The same two initial models, (2, 0, 0) and (1, 0, 1), were tested. The (2, 0, 0) was eventually selected, the same model as for the central Alaska sockeye series. Model fit, however, was the poorest among the time series, as indicated by the  $r^2$  value (0.348). Univariate and intervention model parameter estimates are listed in Table 5, and model statistics in Table 6.

Pink salmon migrate to the ocean in the spring following the year they were spawned and return the following year. Therefore, we tested for interventions in 1948 and 1978. In the one-intervention model, the 1978 intervention was highly significant, but the AR 1 term dropped out as its  $p$ -value increased above 0.05 (to 0.09). The one-intervention model actually had a slightly worse fit than the no intervention model. Had the AR 1 term been retained, however, most diagnostics would have favored the one-intervention model. In the two-intervention model, both interventions (negative in 1948, positive in 1978) were also highly significant ( $p < 0.01$ ). Interestingly, though, no ARIMA terms were significant after inclusion of the two interventions. The interpretation of this result is that Southeast Alaska pink salmon production (as indicated by catch) varies randomly about the various regime levels of production. Nearly half ( $r^2=0.446$ ) of the total variation in Southeast Alaska pink salmon catch was accounted for by the two interventions.

The mean change in catch under the one-intervention model was 12.378 million, from a level of 15.280 million for the 1925-1977 period to a level of 27.658 million for the 1978-1992 period (Fig. 6). Estimated average catch under the two-intervention model decreased by 17.169 million (from 26.678 to 9.509) from the 1925-1947 period to the 1948-1977 period and then increased by 16.480 (to 25.989) million during the 1978-1992 period.

### **Central Alaska pink**

The central Alaska pink time series required a square-root transformation to stabilize the variance. Both the ACF and PACF of the transformed series show significant correlation at lags 1 and 2, indicating a mixed ARMA process. The best model we found was a (1,0,2) model with no MA(1) term. Parameter estimates and model statistics for the univariate and intervention models are listed in Tables 7 and 8, respectively.

In the one-intervention model, the highly significant step intervention identified in 1978 resulted in a mean level increase of 21.216 million, from 14.829 to 36.045 million (Fig. 7). The two-intervention model resulted in a further improvement of the model fit. Under this model, the mean level of production was 19.156 million during 1925-1947, then dropped by 7.383 million to a level of 11.773 million for the 1948-1977 period, then increased by 25.509 million to reach the modern catch level of 37.282 million.

Incorporation of the interventions reduced both the AR(1) and MA(2) parameters substantially as the “regime effect” accounted for an increasingly large part of the serial correlation. The AR(1) term was highly significant ( $p < 0.01$ ) in the no-intervention model, remained barely significant ( $p \sim 0.05$ ) in the one-intervention model, and was not retained in the two-intervention model, resulting in a (0, 0, 2) model. The MA(2) term reduced in magnitude from -0.566 (no-intervention model) to -0.241 (two-intervention model).

## Discussion

Over the past seven decades, Alaskan salmon populations appear to have alternated between high and low production regimes. We propose that Alaskan salmon are responding to changes in North Pacific climate regimes. Under this hypothesis, each salmon population exhibits a unique smaller-scale variability about some mean level of production during a climatic regime. The transition from one regime to another occurs relatively rapidly, resulting in a shift in the mean production level of Alaskan salmon populations.

In support of this hypothesis, we have demonstrated nearly synchronous production shifts in four regional Alaskan salmon stocks. These stocks include two different species from three widely separated geographic regions. Using the technique of intervention analysis, we identified three production regimes defined by two major production shifts, one in the late 1940s, the other in the late 1970s.

Alaskan pink and sockeye salmon spend the majority of their marine life cycle in the Central Subarctic Domain (CSD; Ware and McFarlane 1989) which encompasses the Gulf of Alaska (Fig. 8). The principal feature within the CSD is the Alaska Gyre, with an area of active upwelling at its core. The southern boundary of the CSD is defined by the Subarctic Current, whose latitudinal location varies yearly (Roden 1991, Ward 1993). During the seaward and return migrations, pink and sockeye salmon pass through the Coastal Downwelling Domain, a region extending from Queen Charlotte Sound to Prince William Sound dominated by the Alaska Current.

Any attempt to link physical processes in the marine environment to Alaskan salmon production must involve oceanographic conditions within these two regions. We now examine the two production-regime shifts in greater detail, summarize the change in production, and consider the evidence for concurrent climate-regime shifts. We then discuss potential mechanisms linking the physics and biology.

### Late 1970s Shift

The increase in salmon production was highly significant in all four time series. In the two-intervention models, the smallest t-value (based on roughly 63 degrees of freedom) of the four late 1970s step intervention variables was 5.492 ( $p < 0.0001$ , southeast pink salmon). Both pink salmon time series showed a significant jump in 1978 to a higher production level. Because of the strength of the change in production, the timing of the intervention could also have been placed in 1977 or 1979, but model diagnostics indicated the best fit occurred in 1978. Additionally, we chose to test for a 1978 effect because, according to our hypothesis, the returning 1976 brood year class, first to be exposed to the new oceanic regime, should be the first to show a regime effect. A similar argument, based on the sockeye salmon life history, should lead to a 1979 or 1980 intervention for the two sockeye salmon time series, depending on whether the returning fish spent two or three years in the ocean. For the western Alaska sockeye, a 1979 intervention was statistically more significant than a 1980 intervention. The reverse was true for central Alaska sockeye.

Each of the four production groups is faced with a unique set of environmental conditions between their freshwater rearing habitat and entry into the marine feeding and migration grounds. The three geographic regions each contain numerous salmon-bearing rivers. Localized factors will, therefore, lead to some amount of unique variability added to the effect of the climatic regime on the population as a whole. This is reflected in the differing ARIMA structures among the four time series as well as the remaining unexplained variance. It is clear, however, that the four stocks entered an era of increased production in the late 1970s and have remained at that level in the 1990s. Combining the four series, we estimate that the increased production resulted in an annual mean catch increase of greater than 69 million salmon. This translates to a threefold difference in production between the previous regime of the late 40s-late 70s and the present regime beginning in the late 70s.

Evidence for the timing and strength of the late 1970s regime shift has been documented in numerous environmental and biological variables (Ebbesmeyer et al. 1991). The most obvious physical manifestations of the late 1970s shift include a strengthening and eastward shift of the Aleutian Low (Trenberth 1990) and warming of the surface waters in the Gulf of Alaska (Royer 1989). Defining the event as the onset of a new regime rather than a temporary system shock reflects the persistence of the new state variables. Most evidence pinpoints the winter of 1976-77 as the critical transition period. The shift appears to have been forced by an increasingly vigorous winter circulation over the North Pacific (Graham 1994), leading to more severe and frequent winter storms (Seymour et al. 1984), decreases in

mid-Pacific sea-surface temperatures (SSTs), and basin-wide decreases in sea-level pressure (Trenberth 1990). The large-scale increase in central Pacific chlorophyll (and thus phytoplankton) during the 1970s has been attributed to persistence of warm SSTs in the summer months (Venrick et al. 1987). The increase in Alaskan air and sea-surface temperatures probably derived from warm air advected from the south by a strengthened Aleutian Low.

Hollowed and Wooster (1992) have hypothesized that the North Pacific alternates between two environmental states, with one transition occurring in 1977. The cool period prior to the transition, what they call a type A regime, is characterized by a weak winter Aleutian Low, enhanced westerly winds in the eastern Pacific, decreased advection into the Alaska Current, and negative coastal SST anomalies. A warm era (type B regime) is characterized by a strong winter Aleutian Low displaced to the east, enhanced southwesterly winds in the eastern Pacific, increased advection into the Alaska Current, and positive coastal SST anomalies.

The mechanisms driving the late 1970s regime shift are the subject of much intensive research. Several hypothesized mechanisms have suggested links between this regime shift in the North Pacific and an abrupt climate shift in the tropical Pacific, which occurred in the late 1970s. Kashiwabara (1987) and Nitta and Yamada (1989) have hypothesized that changes in the tropical Pacific forced the change in North Pacific winter circulation patterns. Trenberth (1990) noted that, in the period between 1976 and 1988, there were three warming El Niño events, but no cooling La Niña events. Graham (1994) holds that the El Niño-La Niña cycle continued but the background state was set to a different state. Miller et al. (1994) were able to reproduce the 1976-77 shift with a general circulation model driven by heat flux input, suggesting that the atmosphere (as opposed to an ocean-atmosphere feedback loop) was the primary force. On the basis of observational analyses, Trenberth and Hurrell (1994) attribute North Pacific atmosphere-ocean variability to both local (atmospheric) and remote (tropical oceanic) processes with mid-latitude feedback serving to emphasize decadal scale variability.

### **Late 1940s Shift**

The negative production shifts identified in the late 1940s were all significant, but of lesser magnitude than those of the late 1970s. The *t*-values for the step interventions in the two-intervention models ranged from 6.45 ( $p < 0.0001$ , southeast pink salmon) to 3.27 ( $p < 0.01$ , central pink salmon). The timing of the interventions we tested were selected in the same manner as for the late 1970s shift. Assuming a climate shift in the winter of 1946-47, the appropriate years to test are 1948 (both pink time series), 1949 (western Alaska sockeye), and 1950 (central Alaska sockeye). We estimate the combined drop in catch following the late 1940s intervention at approximately 30 million salmon annually, a decrease of nearly 50%.

Evidence for an late 1940s regime shift is less confirming than for the late 1970s. To some extent, this may be due to the relative lack of data in comparison with that available for the later event. Also, if the salmon data are indicative of the physical data, the shift in physical variables is expected to be smaller and, therefore, more difficult to detect.

Francis and Hare (1994) found a statistically significant negative step in 1947 in Trenberth and Hurrell's (1994) North Pacific Index, a measure of winter atmospheric variability. Several researchers (Dzerdzevskii 1962, Kutzbach 1970, Kalnicky 1974, Brinkmann 1981) have noted sharp changes in upper level atmospheric circulation patterns occurring in the late 1940s to early 1950s. Balling and Lawson (1982) and Granger (1984) showed that rainfall patterns over the southwestern United States changed in the early 1950s. Rogers (1984) presented average winter air temperatures for Kodiak and Bristol Bay from 1920-1983. With only a few exceptions, coastal Alaskan air temperatures remained anomalously low between the 1946-47 and the 1976-77 winters. Surface-temperature trends in the northern hemisphere were shown by Jones (1988) to be in a cool period between the late 1940s and late 1970s. The frequency and intensity of El Niño-Southern Oscillation events have undergone several changes in the past century (Trenberth 1990; Trenberth and Shea 1987) with strong events between 1880 and 1920, and 1950 and the present, and weak events between 1920 and 1950. Trenberth (1990) also noted the preponderance of cold (La Niña) tropical events during the 1950-1977 period compared with the present (1977-1990) imbalance marked by a greater number of warm (El Niño) events.

Several data sets that we examined dated back only to the late 1940s. While not capable of demonstrating a shift in the late 1940s, they do indicate a similarity of conditions for the 1947-1976

period. Between 1949 and 1976, Emery and Hamilton (1985) classified 22 of 28 North Pacific sea-level pressure patterns as either weak or near normal. Hollowed and Wooster (1992) identified 24 of 31 winter atmospheric circulation patterns between 1946 and 1976 as type A regimes (cool periods).

### **Potential Mechanisms**

Establishing the mechanism whereby salmon production is driven by large-scale climate processes can only proceed by speculation at present. We alluded earlier to the general inability of most studies to establish predictable relationships between environmental variables and salmon survival and production that stand the test of time. Quinn and Marshall (1989), for example, found that inclusion of air and water temperature and freshwater discharge provided limited improvement to their time-series models of southeast Alaska salmon variability.

At least two speculative mechanisms have been advanced to help explain the late 1970s rise in Alaskan salmon production. Rogers (1984) proposed that the increase in catch derived from increased marine survival of migrating salmon in their last winter at sea. Anomalously warm surface temperatures in the Gulf of Alaska altered both the migration paths and timing of returning salmon thus lessening their vulnerability to predators (principally marine mammals). Additional evidence for this hypothesis may be provided by the 1970s and 1980s decline in northern fur seal (*Callorhinus ursinus*) and Steller's sea lion (*Eumetopias jubatus*) (Merrick et al. 1987; York 1987).

The second mechanism relates improved feeding conditions in the Alaska Current and Alaska Gyre to increased salmon production. Brodeur and Ware (1992) documented a twofold increase in zooplankton biomass between the 1950s and 1980s in the subarctic Pacific Ocean. They suggest that the primary beneficiaries of the elevated zooplankton biomass are juvenile salmon that migrate around the coastal margin of the CSD foraging on zooplankton advected to the oceanic shelf. Transport of zooplankton-rich waters derives from increased flow into the Alaska Current from the Subarctic Current (Pearcy 1992). Chelton (1984) has proposed that transport into the California and Alaska Currents fluctuates out of phase. This scenario suggests that the observed decrease in west coast salmon production may be due to poor feeding conditions resulting from decreased advection of subarctic water into the California Current (Pearcy 1992). Francis and Sibley (1991) illustrated opposite trends in production between Gulf of Alaska pink salmon and west coast coho salmon. The nature of the transitions from high (low) to low (high) production in both stocks suggests a single cause.

Perhaps the most interesting feature of the salmon regimes we have identified is the nature of the level of persistence exhibited by the different stocks. Hollowed and Wooster (1992) found synchronous recruitment patterns in several groundfish species corresponding to switches between type A and type B regimes. Strong year-classes apparently derived from the onset of type B regimes. Subsequent year-classes, however, were much smaller. This appears to be quite different from the situation we have documented for Alaskan salmon. In addition, the average duration of type A and B regimes was 7-10 yr, whereas we have identified much longer period regimes based on Alaskan salmon dynamics. This suggests that different components of the North Pacific large marine ecosystem respond to forcing factors of different scales.

Little is known about what causes low-frequency shifts in the structure and dynamics of large marine ecosystems. Margalef (1986) challenges us to develop a new paradigm in this regard. He suggests that infrequent and discontinuous changes in external (physical) energy are the most important factors affecting fluctuations in the biological production of these systems. These inputs, which he refers to as "kicks," disrupt established ecological relationships within an ecosystem.

Dr. John Steele (Woods Hole Oceanographic Institution, Woods Hole, MA 02543, personal communication) puts it another way. He feels that, in the ocean, the variances of biological processes that respond to both physical and biological forcings are inversely proportional to their frequencies. If the variance of a process is forced beyond certain bounds or tolerances, that part of the system "snaps," such as when an earthquake occurs, forcing repercussions throughout the ecosystem. As in the case of an earthquake, many system variables that "snap" at the time of the earthquake demonstrate no aberrant behaviors prior to the earthquake itself. So perhaps it is with large marine ecosystems.

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## Appendix

The following time-series model diagnostic and selection criteria were used.

### Box-Pierce Portmanteau test

The joint null hypothesis  $H_0: \rho_1 = \rho_2 = \dots = \rho_K = 0$  is tested with the statistic

$$(A1) \quad Q = n(n+2) \sum_{k=1}^K \frac{1}{n-k} \hat{\rho}^2(k)$$

The hypothesis of white noise is rejected if  $Q > \chi^2_{\alpha, K-m}$ , where  $K$  is the number of residuals calculated from the model and  $m$  is the number of estimated parameters.

### Mean Absolute Error (MAE)

$$(A2) \quad MAE = \frac{1}{K} \sum_{k=1}^K |a_k|$$

Unbiased residual variance  $\sigma_a^2$

$$(A3) \quad \sigma_a^2 = \frac{RSS}{K-m}$$

where  $RSS$  is the residual sum of squares and  $m$  is the number of estimated model parameters

### Coefficient of determination $r^2$

$$(A4) \quad r^2 = 1 - \frac{RSS}{\sum (z - \bar{z})^2}$$

where  $z$  represents the (possibly) transformed and differenced observed values.

### Akaike's Information Criterion (AIC)

$$(A5) \quad AIC = K \ln \tilde{\sigma}_a^2 + 2m \quad \text{where} \quad \tilde{\sigma}_a^2 = \frac{RSS}{K}$$

where  $RSS$  is the residual sum of squares,  $K$  is the number of residuals,  $m$  is the number of estimated parameters, and  $\sigma_a^2$  is the biased residual variance.

### Schwarz Bayesian Criterion (SBC)

$$(A6) \quad SBC = K \ln \tilde{\sigma}_a^2 + m \ln K$$

where the parameters have the same interpretation as for the AIC.

Table 1. Univariate and intervention ARIMA models with parameter estimates and associated standard errors developed for western Alaska sockeye salmon. Standard errors are given in parentheses below the equations.

Model	Parameter estimates and standard errors
Univariate	$(1 - 0.538B - 0.505B^5 + 0.369B^6)\sqrt{Y_t} = 1.209 + a_t$ (0.107) (0.111) (0.122) (0.107)
One intervention (1979)	$(1 - 0.299B - 0.499B^5 + 0.253B^6)\sqrt{Y_t} = 1.468 + a_t + 2.036I_t^{1979}$ (0.121) (0.109) (0.131) (0.105) (0.415)
Two interventions (1949, 1979)	$(1 + 0.305B^3 - 0.377B^5 + 0.225B^6)\sqrt{Y_t} = 4.206 + a_t - 0.754I_t^{1949} + 2.192I_t^{1979}$ (0.121) (0.114) (0.117) (0.161) (0.188) (0.223)

Table 2. Summary statistics for univariate and intervention ARIMA models developed for western Alaska sockeye salmon. MAE = mean absolute error of fitted values,  $\sigma_a^2$  = unbiased residual variance,  $r^2$  = coefficient of determination, AIC = Akaike's Information Criterion, SBC = Schwarz's Bayesian Criterion, and Q = portmanteau residual autocorrelation test (up to lag 20) and associated  $p$ -value. All statistics are calculated in the transformed metric.

Model	MAE	$\sigma_a^2$	$r^2$	AIC	SBC	Q	p value
Univariate	0.741	0.836	0.459	186.6	195.5	15.17	0.767
One intervention	0.632	0.667	0.575	172.0	183.1	13.64	0.848
Two interventions	0.603	0.607	0.623	166.4	179.7	17.43	0.625

Table 3. Univariate and intervention ARIMA models with parameter estimates and associated standard errors developed for central Alaska sockeye salmon. Standard errors are given in parentheses below the equations.

Model	Parameter estimates and standard errors
Univariate	$(1-0.568B - 0.316B^2)\ln Y_t = 0.216 + a_t$ (0.117) (0.121) (0.034)
One intervention (1980)	$(1-0.572B)\ln Y_t = 0.655 + a_t + 0.917I_t^{1980}$ (0.102) (0.040) (0.188)
Two interventions (1950, 1980)	$(1-0.310B)\ln Y_t = 1.197 + a_t - 0.409I_t^{1950} + 1.145I_t^{1980}$ (0.120) (0.058) (0.112) (0.135)

Table 4. Summary statistics for univariate and intervention ARIMA models developed for central Alaska sockeye salmon. MAE = mean absolute error of fitted values,  $\sigma_a^2$  = unbiased residual variance,  $r^2$  = coefficient of determination, AIC = Akaike's Information Criterion, SBC = Schwarz's Bayesian Criterion, and Q = portmanteau residual autocorrelation test (up to lag 20) and associated  $p$ -value. All statistics are calculated in the transformed metric.

Model	MAE	$\sigma_a^2$	$r^2$	AIC	SBC	Q	p value
Univariate	0.255	0.101	0.644	41.3	47.9	15.14	0.768
One intervention	0.234	0.094	0.672	35.7	42.4	14.13	0.824
Two interventions	0.213	0.087	0.704	31.1	40.1	9.92	0.970

Table 5. Univariate and intervention ARIMA models with parameter estimates and associated standard errors developed for southeast Alaska pink salmon. Standard errors are given in parentheses below the equations.

Model	Parameter estimates and standard errors
Univariate	$(1 - 0.277B - 0.410B^2)\ln Y_t = 0.906 + a_t$ (0.112) (0.115) (0.073)
One intervention (1978)	$(1 - 0.495B^2)\ln Y_t = 1.377 + a_t + 0.593I_t^{1978}$ (0.108) (0.084) (0.310)
Two interventions (1948,1978)	$\ln Y_t = 3.284 + a_t - 1.032I_t^{1948} + 1.005I_t^{1978}$ (0.121) (0.160) (0.183)

Table 6. Summary statistics for univariate and intervention ARIMA models developed for southeast Alaska pink salmon. MAE = mean absolute error of fitted values,  $\sigma_a^2$  = unbiased residual variance,  $r^2$  = coefficient of determination, AIC = Akaike's Information Criterion, SBC = Schwarz's Bayesian Criterion, and Q = portmanteau residual autocorrelation test (up to lag 20) and associated  $p$ -value. All statistics are calculated in the transformed metric.

Model	MAE	$\sigma_a^2$	$r^2$	AIC	SBC	Q	p value
Univariate	0.484	0.397	0.348	133.7	140.3	14.43	0.808
One intervention	0.515	0.413	0.317	136.3	143.0	22.18	0.331
Two interventions	0.452	0.334	0.446	121.4	128.1	18.02	0.586

Table 7. Univariate and intervention ARIMA models with parameter estimates and associated standard errors developed for central Alaska pink salmon. Standard errors are given in parentheses below the equations.

Model	Parameter estimates and standard errors
Univariate	$(1 - 0.482B)\sqrt{Y_t} = 2.238 + (1 + 0.566B^2)a_t$ (0.110)      (0.178)      (0.117)
One intervention (1978)	$(1 - 0.252B)\sqrt{Y_t} = 2.893 + (1 + 0.362B^2)a_t + 2.089I_t^{1978}$ (0.128)      (0.163)      (0.135)      (0.433)
Two interventions (1948, 1978)	$\sqrt{Y_t} = 4.377 + (1 + 0.241B^2)a_t - 0.946I_t^{1948} + 2.675I_t^{1978}$ (0.219)      (0.122)      (0.289)      (0.327)

Table 8. Summary statistics for univariate and intervention ARIMA models developed for central Alaska pink salmon. MAE = mean absolute error of fitted values,  $\sigma_a^2$  = unbiased residual variance,  $r^2$  = coefficient of determination, AIC = Akaike's Information Criterion, SBC = Schwarz's Bayesian Criterion, and Q = portmanteau residual autocorrelation test (up to lag 20) and associated  $p$ -value. All statistics are calculated in the transformed metric.

Model	MAE	$\sigma_a^2$	$r^2$	AIC	SBC	Q	p value
Univariate	0.726	0.915	0.583	191.2	197.9	9.63	0.974
One intervention	0.628	0.797	0.653	181.9	190.8	10.81	0.951
Two interventions	0.608	0.745	0.672	177.1	1846.0	20.03	0.456

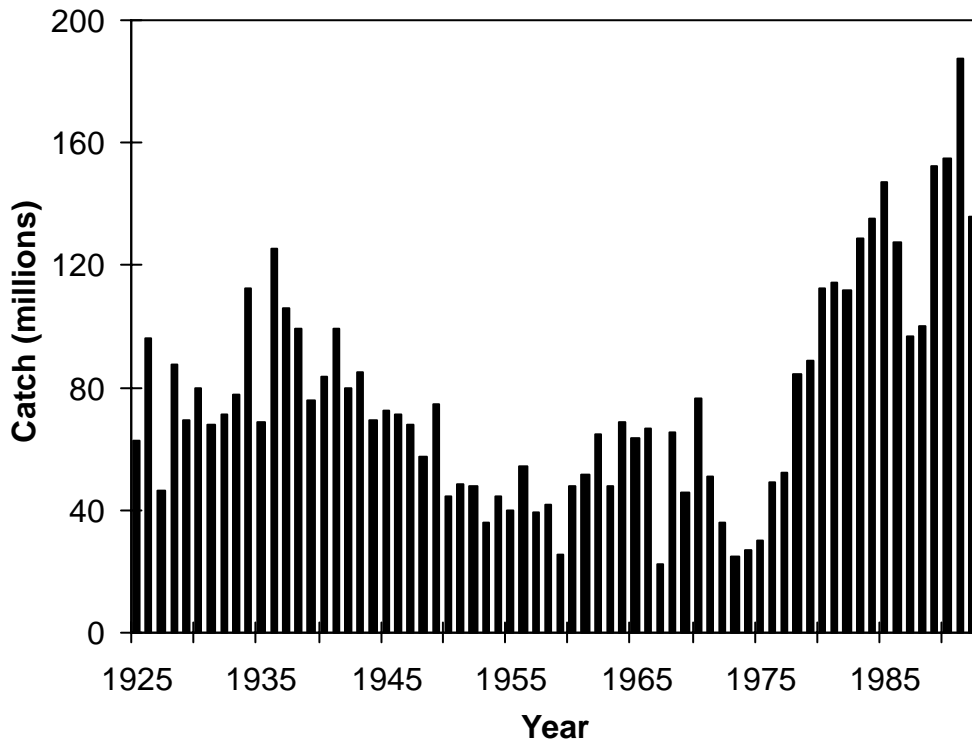


Figure 1. Trend in total Alaskan salmon catch, 1925-1992.

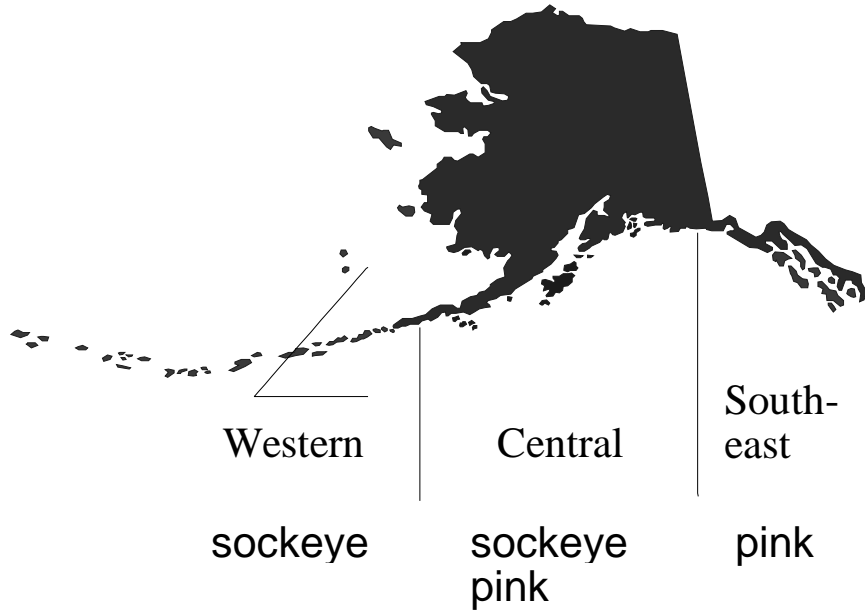


Fig. 2. ADFG statistical areas and regional salmon stocks used in this study.

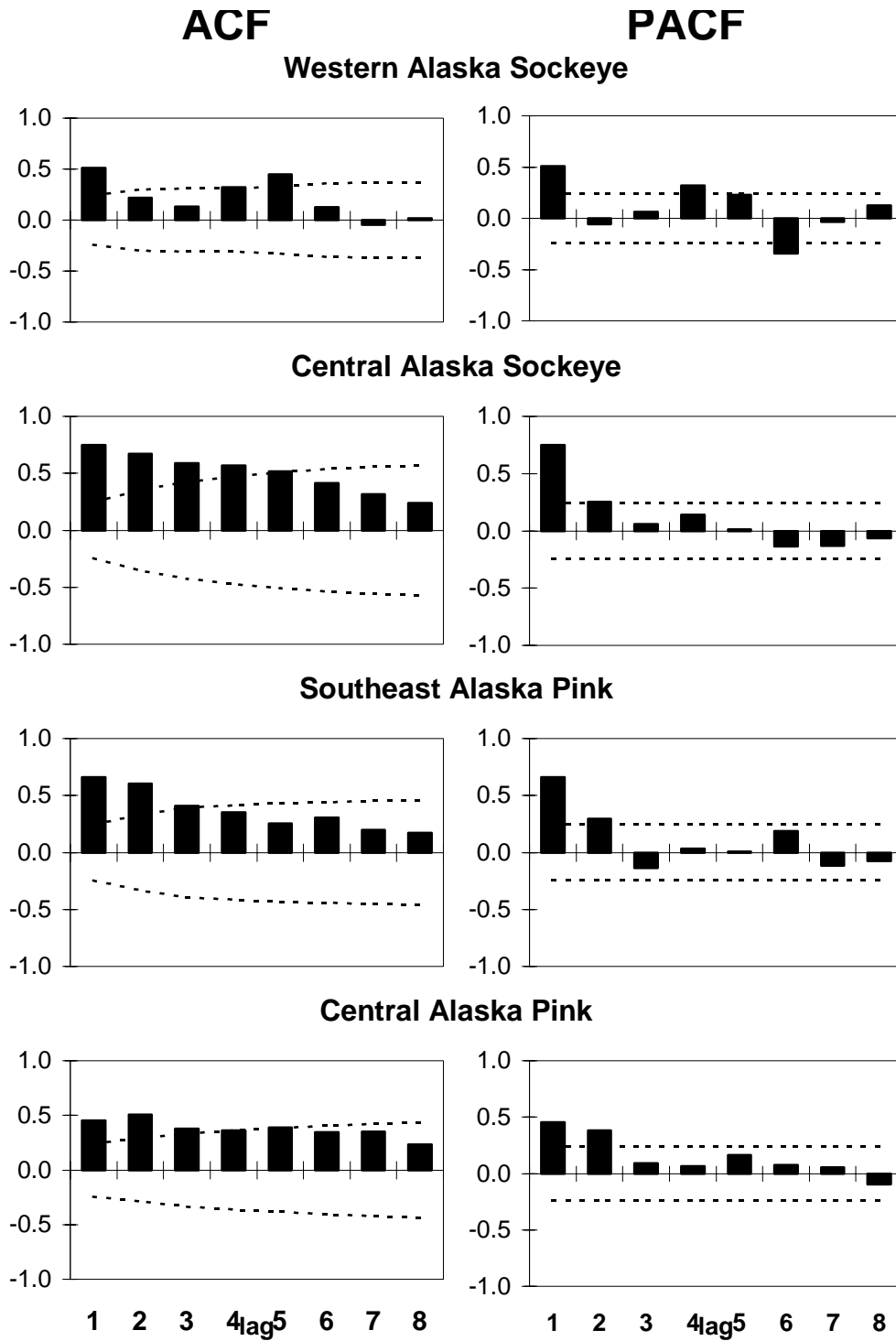


Fig. 3. Plots of the autocorrelation (ACF) and partial autocorrelation (PACF) functions for the four salmon time series. The ACF and PACF are computed for the appropriately differenced and transformed time series. The horizontal lines represent  $\pm 2$  standard errors of the sample lag autocorrelation estimates.

## Western Alaska sockeye

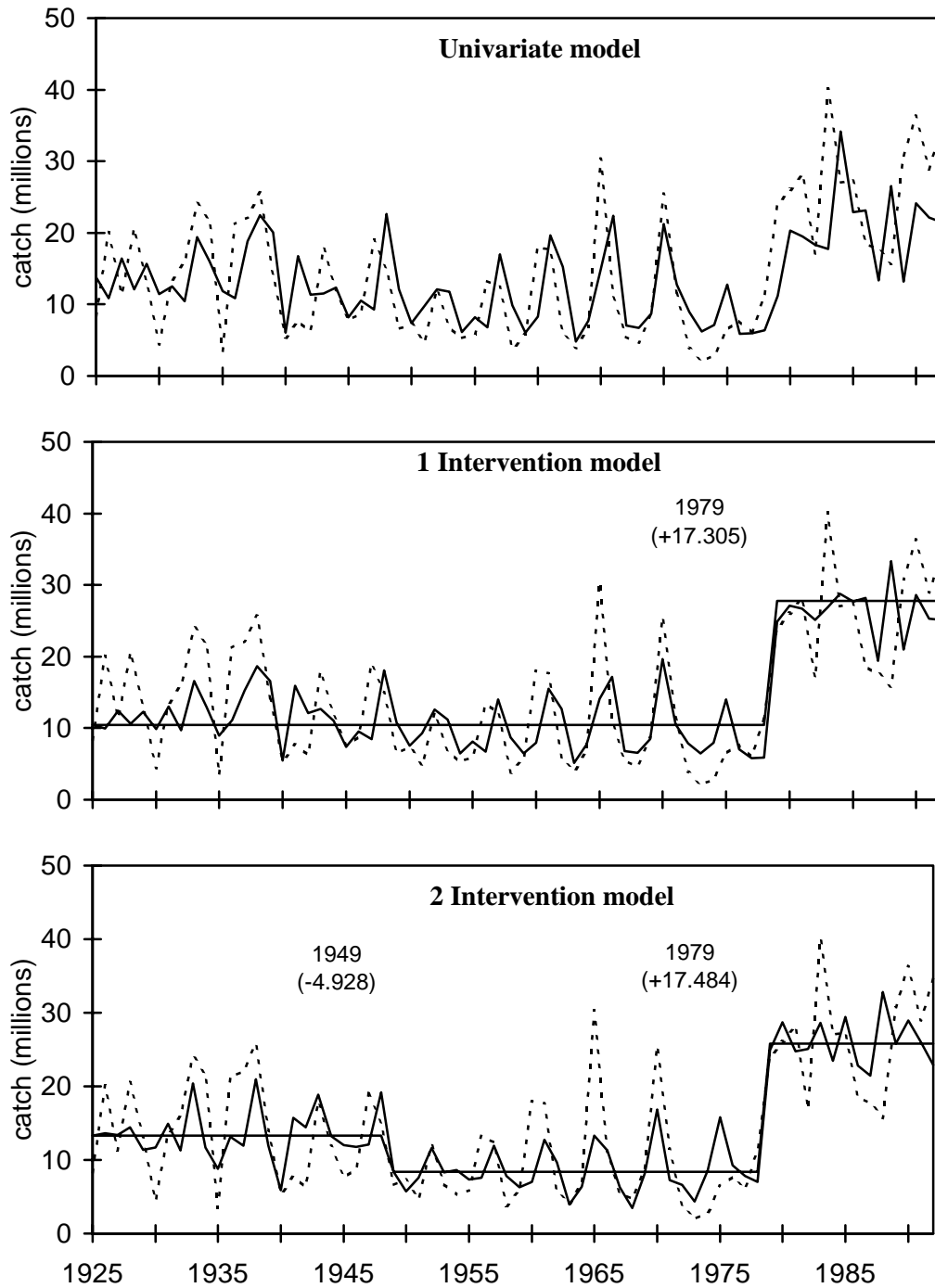


Fig. 4. Plots of model fits for ARIMA and intervention models developed for western Alaska sockeye salmon time series, 1925-1992. Landings data are indicated by dashed lines, fitted values by thick lines. Estimated means before and after interventions are shown by straight lines. Timing of the step interventions and resultant change in mean are also shown.

## Central Alaska sockeye

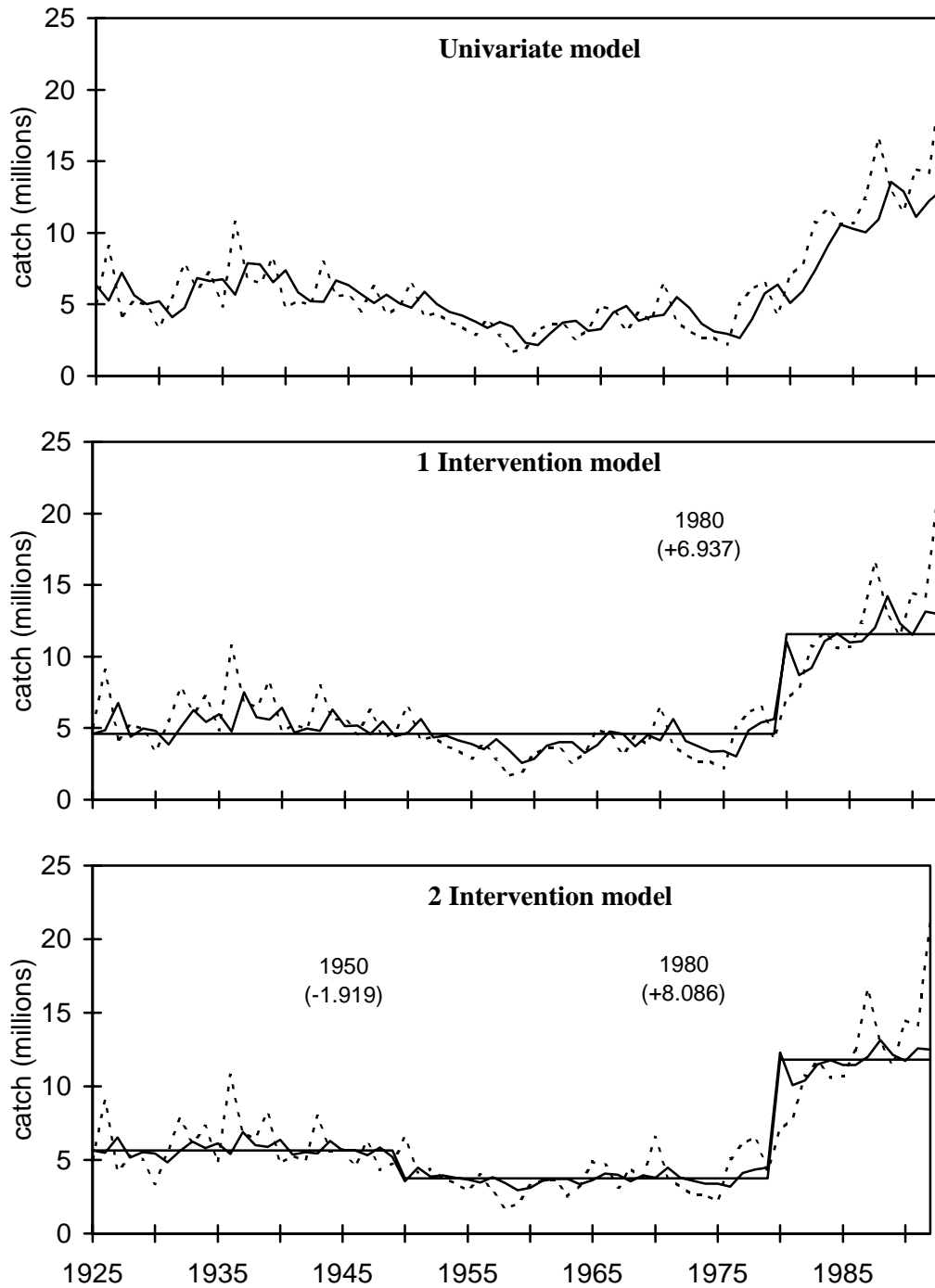


Fig. 5. Plots of model fits for ARIMA and intervention models developed for central Alaska sockeye salmon time series, 1925-1992. Landings data are indicated by dashed lines, fitted values by thick lines. Estimated means before and after interventions are shown by straight lines. Timing of the step interventions and resultant change in mean are also shown.

## Southeast Alaska pink

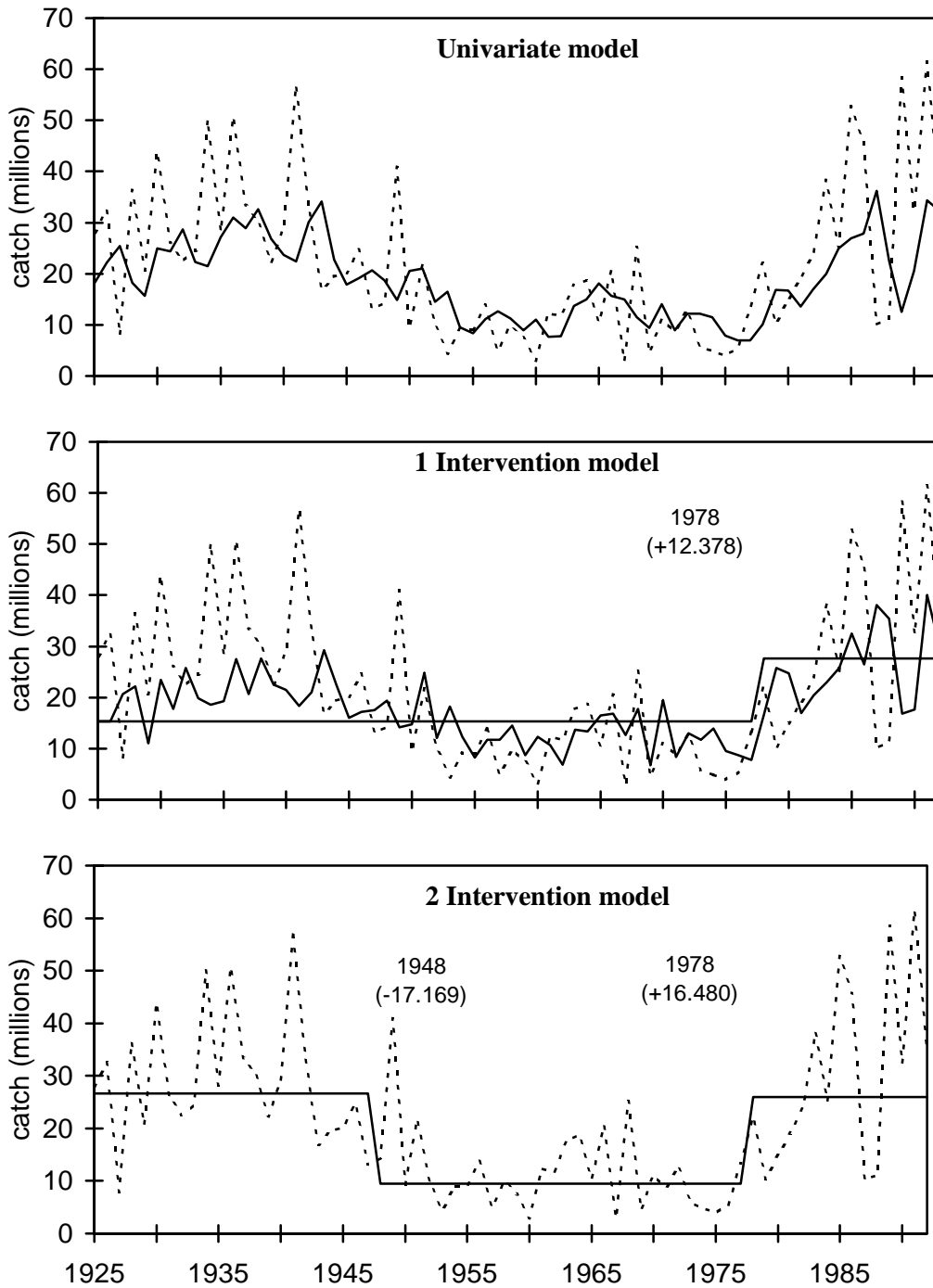


Fig. 6. Plots of model fits for ARIMA and intervention models developed for southeast Alaska pink salmon time series, 1925-1992. Landings data are indicated by dashed lines, fitted values by thick lines. Estimated means before and after interventions are shown by straight lines. Timing of the step interventions and resultant change in mean are also shown.

## Central Alaska pink

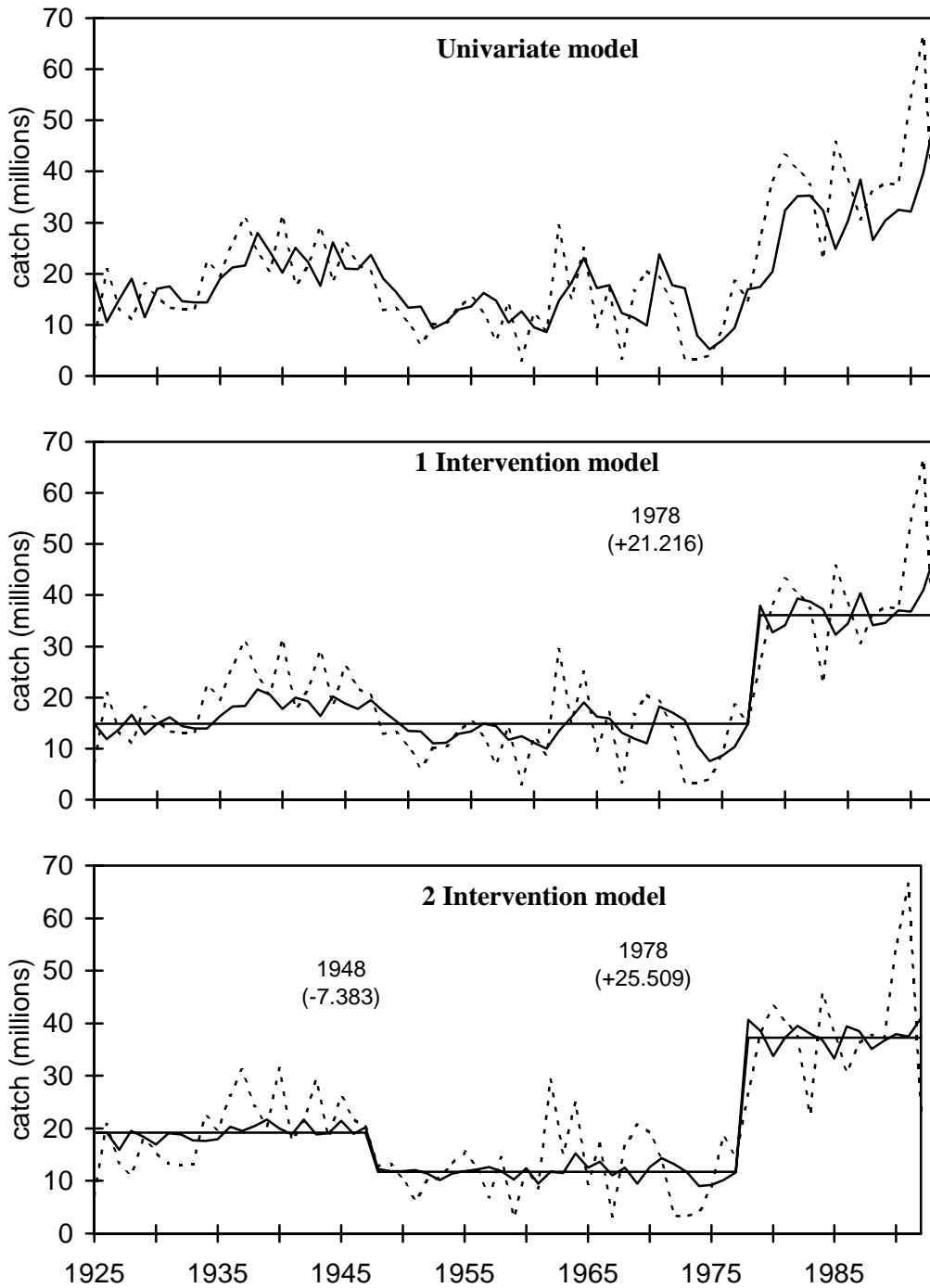


Fig. 7. Plots of model fits for ARIMA and intervention models developed for central Alaska pink salmon time series, 1925-1992. Landings data are indicated by dashed lines, fitted values by thick lines. Estimated means before and after interventions are shown by straight lines. Timing of the step interventions and resultant change in mean are also shown.

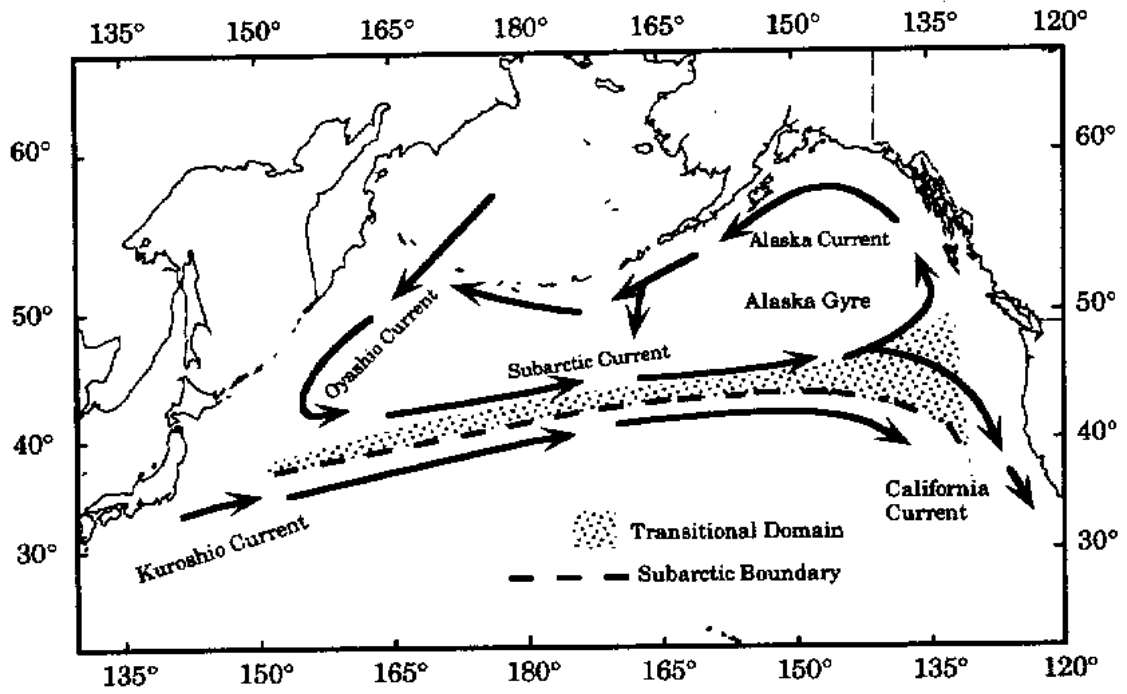


Fig. 8. Summary of major oceanographic features of the North Pacific.