Climate change and salmon production in the Northeast
Pacific Ocean
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ABSTRACT
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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;
Pearcy 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. Pearcy 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 (Pearcy 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; Mendelssohn 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 Mendelssohn 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)

   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 (l=0.5), natural
logarithm (l=0.0), and inverse (l=-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.

   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.

   is a seasonal integrating factor(s) where s is the lag at which the Dth 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.

   plays different roles depending on the value of d (order of differencing). For d = 0, q0
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 ³ 1, q0 is called the deterministic trend and is often omitted unless clearly called for (Wei 1990, p. 72).

at is a random error component assumed to be normally independently distributed with mean 0 and constant variance s2a.

B is the backshift operator. By convention it is a special notation used to simplify the representation of lagged values: Byt = yt-1,
Bsyt = yt-s. Note also the following definition: Ñ = 1 - B, thus differencing is often represented by: Ñyt = (1 - B)yt.

　　is the autoregressive polynomial of the form (1 - f1B - f2B2 - ... - fpBp). 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 yt = f1yt-1 + f2yt-2 + ... + fPyt-P + at..
An autoregressive process of order p is abbreviated AR(p), and lower orders than p need not be non-zero.

　　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.

　　is the moving average polynomial of the form (1 - q1B - q2B2 - ... - qqBq). The moving average term models the
persistence of random effects over time and can be written as yt = at + q1at-1 + q2at-2 + ... + qpat-p. A moving average
process of order q is abbreviated MA(q), and lower orders than q need not be non-zero.

　　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.

　　represents the jth intervention and is analogous to a dummy variable in regression. Interventions can be either step (I = 1 for
t ³ 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.

is a polynomial of the form (w0 - w1B - w2B2 - ... - wsBs) representing the initial impact of the intervention.

is a polynomial of the form (1 - d1B - d2B2 - ... - drBr) representing the long-term impact of the intervention.

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) x (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) x (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 at 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 $s2a$, 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)5. 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)5 x (0, 0, 1)3 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 (r2=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 r2 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 (r2=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 ~ 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 (Dzerdzeevskii 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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References

Akaike, H. 1974. A new look at statistical model identification. IEEE Trans. Autom. Control AC-19: 716-723.

Alaska Department of Fish and Game. 1991. Alaska commercial salmon catches, 1878-1991. Reg. Info. Rep. 5J91-16.
Division of . Commercial Fish, Juneau, AK. 88 p.

Automatic Forecasting Systems, Inc. 1992. AUTOBOX. P.O. Box 563, Hatboro, PA 19040, USA.

Balling, R.C., Jr. and M.P. Lawson. 1982. Twentieth century changes in winter climatic conditions. Climatic Change 4: 57-69.

Baumgartner, T.R., A. Soutar, and V. Ferreira-Bartrina. 1992. Reconstruction of the history of Pacific sardine and northern
anchovy populations over the past two millenia from sediments of the Santa Barbara Basin, California. Calif. Coop. Oceanic
Fish. Invest. Rep. 33: 24-40.

Beamish, R. J. and D.R. Bouillon. 1994. Marine fish production trends off the Pacific Coast of Canada and the United States,
p. xx-xx. In R.J. Beamish [ed.] Ocean Climate and Northern Fish Populations. Ca. Spec. Publ. Fish. Aquat. Sci. 121.

Beamish, R.J. and G.A. McFarlane [ed.] 1989. Effects of ocean variability on recruitment and an evaluation of parameters
used in stock assessment models. Can. Spec. Publ. Fish Aquat. Sci. 108.

Boudreault, F.-R., J.-N. Dupont, and C. Sylvain. 1977. Modèles linéaires de prédiction des débarquements de homard aux
Iles-de-la-Madeleine (Golfe du Saint-Laurent). J. Fish. Res. Board Can. 34: 379-383.

Box, G.E.P., and D.R. Cox. 1964. An analysis of transformations. J. R. Stat. Soc. Ser. B 26: 211-243.

Box, G.E.P., and G.M. Jenkins. 1976. Time series analysis: forecasting and control, Revised edition Holden-Day, San
Francisco, CA. 575 p.

Box, G.E.P., and D.A. Pierce. 1970. Distribution of residual autocorrelations in autoregressive-integrated moving average time
series models. J. Am. Stat. Assoc. 65: 1509-1526.

Box, G.E.P., and G.C.Tiao. 1975. Intervention analysis with applications to economic and environmental problems. J. Am.
Stat. Assoc. 70: 70-79.

Brinkmann, W.A.R. 1981. Sea level pressure patterns over eastern North America, 1899-1976. Mon. Weather. Rev.
109:1305-1317.

Brodeur, R.D. and D.M. Ware. 1992. Interannual and interdecadal changes in zooplankton biomass in the subarctic Pacific
Ocean. Fish. Oceanogr. 1: 32-38.

Calderon-Aguilera, L.E. 1991. An autoregressive model of the temperature-growth relationship for the western Mediterranean
blue whiting Micromesistius poutassou. Ecol. Modeling 56: 47-61.

Campbell, A., D.J. Noakes, and R.W. Elner. 1991. Temperature and lobster, Homarus americanus, yield relationships. Can.
J. Fish. Aquat. Sci. 48: 2073-2082.

Carpenter, S.R. 1990. Large-scale perturbations: opportunities for innovation. Ecology 71: 2038-2043.

Chang, I. and G.C. Tiao. 1983. Estimation of time series parameters in the presence of outliers. Tech. Rep. 8. Statistics
Research Center, University of Chicago,.Chicago, IL.

Chelton, D.B. 1984. Short-term climate variability in the northeast Pacific Ocean, p. 87-99. In W.G. Pearcy [ed.] The
influence of ocean conditions on the production of salmonids in the north Pacific. Oregon State Univ. Sea Grant, Corvallis, OR.

Cohen, Y., and J. N. Stone. 1987. Multivariate time series analysis of the Canadian fisheries system in Lake Superior. Can. J.
Fish. Aquat. Sci. 44(Suppl. 2): 171-181.

Cross, B.A., D.R. Bernard, and S.L. Marshall. 1983. Returns-per-spawner ratios for sockeye salmon in upper Cook Inlet,
Alaska. Alaska Dept. Fish Game Inform. Leafl. 221: 82 p.

Dunn, J.E., and C.O. Murphy. 1976. A study of the feasibility of ecosystems modelling of Beaver Reservoir. Univ. Arkansas
Stat. Lab. Tech. Rep. 1. 87 p.

Dzerdzeevskii. B. 1962. Fluctuations of climate and general circulation of the atmosphere in extra-tropical latitudes of the
Northern Hemisphere and some problems of dynamic climatology. Tellus 14: 328-336.

Ebbesmeyer, C.C., D.R. Cayan, D.R. Milan, F.H. Nichols, D.H. Peterson and K.T. Redmond. 1991. 1976 step in the Pacific
climate: forty environmental changes between 1968-1975 and 1977-1984, p.129-141. In J.L. Betancourt and V.L. Sharp
[ed.] Proceedings of the Seventh Annual Pacific Climate (PACLIM) Workshop, April 1990, Asilomar, CA. California
Department of Water Resources Interagency Ecological Studies Program Tech. Rep. 26.

Eggers, D. M. and D. E. Rogers. 1987. The cycle of runs of sockeye salmon (Oncorhynchus nerka) to the Kvichak River,
Bristol Bay, Alaska: cyclic dominance or depensatory fishing?,p. 343-366. In H.D. Smith, L. Margolis, and C.C. Wood [ed.]
Sockeye salmon (Oncorhynchus nerka) population biology and future management. Can. Spec. Publ. Fish. Aquat. Sci. 96.

Emery, W.J. and K. Hamilton. 1985. Atmospheric forcing of interannual variability in the northeast Pacific Ocean: connections
with El Niño. J. Geophys. Res. 90: 857-868.

Fogarty, M. J. 1988a. Time series models of the Maine lobster fishery: the effect of temperature. Can. J. Fish. Aquat. Sci. 45:
1145-1153.

1988b. Forecasting yield and abundance of exploited invertebrates. In J.F. Caddy [ed.] The scientific basis of shellfish
management. John Wiley & Sons, New York and London.

Francis, R.C. and S.R. Hare. 1994. Decadal-scale regime shifts in the large marine ecosystems of the North-east Pacific: a
case for historical science. Fish. Oceanogr. 3: 1-13.

Francis, R.C. and T.H. Sibley. 1991. Climate change and fisheries: what are the real issues? Northwest Environ. J. 7: 295-307.

Graham, N. E. 1994. Decadal-scale climate variability in the 1970s and 1980s: observations and model results. Clim. Dyn. 10:
135-159.

Granger, O.E. 1984. Twentieth-century climate anomaly patterns over the southwestern United States. Phys. Geogr. 5:
164-185.

Harris, C. 1989. The effects of international treaty changes on Japan's high seas salmon fisheries, with emphasis on their
catches of North American sockeye salmon, 1972-1984. Ph. D. Dissertation, Univ. Washington, 231 p.

Harvey, A.C. 1989. Forecasting, structural time series models and the Kalman filter. Cambridge University Press. Cambridge.
554 p.

Hollowed, A.B. and W.S. Wooster. 1992. Variability of winter ocean conditions and strong year classes of Northeast Pacific
groundfish. ICES mar. Sci. Symp. 195: 433-444.

Jeffries, P., A. Keller, and S. Hale. 1989. Predicting winter flounder (Pseudopleuronectes americanus) catches by time series
analysis. Can. J. Fish. Aquat. Sci. 46: 650-659.

Jenkins, G.M. 1979. Practical experiences with modelling and forecasting time series. Gwilym Jenkins and Partners (Overseas)
Ltd., Jersey, UK.

Jensen, A.L. 1985. Time series analysis and forecasting of Atlantic menhaden catch and CPUE. N. Am. J. Fish. Manage. 5:
78-85.

Jones, P.D. 1988. Hemispheric surface air temperature variations: recent trends and an update to 1987. J. Climate 1: 654-660.

Kalman, R.E. 1960. A new approach to linear filtering and prediction problems. ASME J. Basic. Eng. 82: 34-45.

Kalman, R.E., and R.S. Bucy. 1961. New results in linear filtering and prediction theory. ASME J. Basic Eng. 83: 95-107.

Kalnicky, R.A. 1974. Climatic change since 1950. Ann. Assoc. Am. Geogr. 64: 100-112.

Kashiwabara, T. 1987. On the recent winter cooling in the north Pacific. Tenki 34: 777-781. (In Japanese)

Kirkley, J.E., M. Pennington, and B.E. Brown. 1982. A short-term forecasting approach for analyzing the effects of harvesting
quotas: application to the Georges Bank yellowtail flounder (Limanda ferruginea)

fishery. J. Cons. Cons. int. Explor. Mer 40:
173-175.

Kutzbach, J.E. 1970. Large-scale features of monthly mean northern hemisphere anomaly
maps of sea-level pressure. Mon.
Weather. Rev. 98: 708-712.

Madenjian, C.P., D.J. Jude, and F.J. Tesar. 1986. Intervention analysis of power plant
impact on fish populations. Can. J.
Fish. Aquat. Sci. 43: 819-829.

Margalef, R. 1986. Reset successions and suspected chaos in models of marine
populations, p. 321-343. In T. Wyatt, and
M.G. Larrañeta [ed.] International Symposium on Long Term Changes in Marine Fish
Populations, 18-21 Nov. 1986, Vigo,
Spain, 1986.

Mathews, S. B.1984. Variability of marine survival of Pacific salmonids: a review, p.
167-182. In W.G. Pearcy [ed.] The
influence of ocean conditions on the production of salmonids in the north Pacific. Sea
Grant Publ., Oregon State University.
Corvallis, OR.

Mendelssohn, R. 1981. Using Box-Jenkins models to forecast fishery dynamics:
identification, estimation, and checking. Fish.
Bull. U.S. 78: 887-896.

Mendelssohn, R., and P. Cury. 1987. Fluctuations of a fortnightly abundance index of the
Ivorian coastal pelagic species and
associated environmental conditions. Can. J. Fish. Aquat. Sci. 44: 408-421.

Mendelssohn, R., and P. Cury. 1989. Temporal and spatial dynamics of a coastal pelagic
species, Sardinella madarensis off
the Ivory Coast. Can. J. Fish. Aquat. Sci. 46: 1686-1697.

Merrick, R.L., T.R. Loughlin, and D.G. Calkins. 1987. Decline in abundance of the
northern sea lion, Eumetopias jubata, in
Alaska 1956-86. Fish Bull. 85: 351-365.

Miller, A.J., D.R. Cayan, T.P. Barnett, N.E. Graham, and J.M. Oberhuber. 1994.
Interdecadal variability of the Pacific Ocean:
model response to observed heat flux and wind stress anomalies. Clim. Dyn. 9: 287-302.

Moran, P.A.P. 1949. The statistical analysis of sunspot and lynx cycles. J. Anim. Ecol.
18: 115-116.

Murphy, C., and J. E. Dunn. 1977. Use of transfer function models to forecast sport fish harvest in Beaver Reservoir. Univ.
Arkansas Stat. Lab. Tech. Rep. 6. 150 p.

Newton, H. J. 1988. TIMESLAB: a time series analysis laboratory. Wadsworth & Brooks/Cole Publishing Co., Pacific
Grove, CA. 623 p.

Nitta, T., and S. Yamada. 1989. Recent warming of tropical sea surface temperature and its relationship to the northern
hemisphere circulation. J. Meteorol. Soc. Jpn 67: 375-383.

Noakes, D. 1986. Quantifying changes in British Columbia Dungeness crab (Cancer magister) landings using intervention
analysis. Can. J. Fish. Aquat. Sci. 43: 634-639.

Noakes, D.J., and A. Campbell. 1992. Use of geoduck clams to indicate changes in the marine environment of Ladysmith
Harbour, British Columbia. Environmetrics 3(1):81-97.

Noakes, D., D.W. Welch, and M. Stocker. 1987. A time series approach to stock-recruitment analysis: transfer function noise
modelling. Nat. Resour. Modell. 2: 213-233.

Pacific Fishing. 1994. 1994 Yearbook. Vol XV, No. 3.

Pacific Salmon Commission. 1991 Second report on the parties' estimates of salmon interceptions. Rep. JIC (91)-1. Joint
Interception Committee, Pacific Salmon Commission, Vancouver, B.C.

Parzen, E. 1981. Time series model identification and prediction variance horizon, p.415-447. In D.F. Findley [ed.]
Proceedings of the Second Applied Time Series Symposium, March 3-5, 1980, Tulsa OK. Academic Press, NY.

Pearcy, W.G. [ed.] 1984. The influence of ocean conditions on the production of salmonids in the north Pacific. Sea Grant
Publ., Oregon State University, Corvallis, OR.

Pearcy, W.G. 1992. Ocean ecology of north Pacific salmonids. University of Washington Press, Seattle, WA. 179 p.

Pennington, M. 1985. Estimating the relative abundance of fish from a series of trawl surveys. Biometrics 41: 197-202.

Quinn, T.J., II, and R.P. Marshall. 1989. Time series analysis: quantifying variability and correlation in SE Alaska salmon
catches and environmental data, p. 67-80. In R.J. Beamish and G.A. McFarlane [ed.] Effects of ocean variability on
recruitment and an evaluation of parameters used in stock assessment models. Can. Spec. Publ. Fish. Aquat. Sci. 108.

Roden, G.I. 1991. Subarctic-subtropical transition zone of the north Pacific: large-scale aspects and mesoscale structure, p.
1-38. In J. Wetherall [ed.] Biology, oceanography, and fisheries of the north Pacific transition zone and subarctic frontal zone.
NOAA Tech. Rep. NMFS 105.

Rogers, D.E. 1984. Trends in abundance of northeastern Pacific stocks of salmon, p. 100-127. In W. G. Pearcy. [ed.] The
influence of ocean conditions on the production of salmonids in the North Pacific. Oregon State University Press, Corvallis,
OR.

Royer, T. C. 1989. Upper ocean temperature variability in the northeast Pacific Ocean: is it an indicator of global warming? J.
Geophys. Res. 94: 18 175 - 18 183.

Saila, S.B., M. Wigbout, and R.J. Lermit. 1980. Comparison of some time series models for the analysis of fisheries data. J.
Cons. Cons. int. Explor. Mer 39: 44-52.

Schwarz, G. 1978. Estimating the dimension of a model. Ann. Stat. 6: 461-464.

Seymour, R.J., R.R. Strange, D.R. Cayan, and R.A. Nathan. 1984. Influence of El Niños on California's wave climate, In
Proceedings 19th International Conference on Coastal Engineering, American Society of Coastal Engineering, Houston, TX.

Shepard, M.P., C.D. Shepard, and A.W. Argue. 1985. Historic statistics of salmon production around the Pacific rim. Can.
MS Rep. Fish. Aquat. Sci. 1819. 297 p.

Shepherd, J.G., J.G. Pope, and R.D. Cousens. 1984. Variations in fish stocks and hypotheses concerning their links to climate.
Rapp. P.-v. Réun. Cons. int. Explor. Mer 36: 15-26.

SPSS, Inc. 1993. SPSS for Windows: Trends. 444 N. Michigan Ave., Chicago, IL. 60611

Stergiou, K.I. 1989. Modelling and forecasting the fishery for pilchard (Sardina pilchardus) in Greek waters using ARIMA
time-series models. J. Cons. Cons. int. Explor. Mer 46: 16-23.

Stone, J. N., and Y. Cohen. 1990. Changes in species interactions of the Lake Superior fisheries system after the control of
sea lamprey as indicated by time series models. Can. J. Fish. Aquat. Sci. 47: 251-261.

Trenberth, K.E. 1990. Recent observed interdecadal climate changes in the northern hemisphere. Bull. Am. Meteorol. Soc. 71:
988-993.

Trenberth, K.E., and J.W. Hurrell. 1994. Decadal atmosphere-ocean variations in the Pacific. Clim. Dyn. 9: 303-319.

Trenberth, K.E., and D.J. Shea. 1987. On the evolution of the Southern Oscillation. Mon. Weather. Rev. 115: 3078-3096.

Tsai, C.-F, and A.-L. Chai. 1992. Short-term forecasting of the striped bass (Morone saxatilis) commercial harvest in the
Maryland portion of Chesapeake Bay. Fish. Res. 15: 67-82.

Tsay, R.S., and G.C. Tiao. 1984. Consistent estimates of autoregressive parameters and extended sample autocorrelation
function for stationary and nonstationary ARMA models. J. Am. Stat. Assoc. 79: 84-96.

Venrick, E.L., J.A. McGowan, D.R. Cayan, and T.L. Hayward. 1987. Climate and chlorophyll a: long-term trends in the
central north Pacific Ocean. Science (Wash., D.C.) 238: 70-72.

Ward, M.B. 1993. The physical dynamics of the North Pacific Ocean and its relation to salmon (Oncorhynchus spp.)
production. M.S. Thesis, Univ. Washington. 109 p.

Ware, D.M., and G.A. McFarlane. 1989. Fisheries production domains in the northeast Pacific Ocean, p.359-379. In R.J.
Beamish and G.A. McFarlane [ed.] Effects of ocean variability on recruitment and an evaluation of parameters used in stock
assessment models. Can. Spec. Publ. Fish. Aquat. Sci. 108.

Wei, W.W.S. 1990. Time series analysis, univariate and multivariate methods. Addison-Wesley, Redwood City, CA. 478 p.

Woodward, W., and H.L. Gray. 1981. On the relationship between the S array and the Box-Jenkins method of model
identification. J. Am. Stat. Assoc. 76: 579-587.

York, A. E. 1987. Northern fur seal, Callorhinus ursinus, eastern Pacific population (Pribilof Islands, Alaska, and San Miguel
Island, California), p. 9-21. In J.P. Croxall and R.L. Gentry [ed.] Status, Biology and Ecology of Fur Seals. Proceedings of an
International Symposium and Workshop, 23-27 April, 1984, Cambridge, UK, NOAA Tech. Rep. NMFS 51.

Appendix

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

Box-Pierce Portmanteau test

The joint null hypothesis Ho: $r_1 = r_2 = ... = r_K = 0$ is tested with the statistic

(A1)

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

Mean Absolute Error (MAE)

(A2)

Unbiased residual variance s^2_a

(A3)
where RSS is the residual sum of squares and m is the number of estimated model parameters

Coefficient of determination r^2

(A4)
where z represents the (possibly) transformed and differenced observed values.

Akaike's Information Criterion (AIC)

(A5)

where RSS is the residual sum of squares, K is the number of residuals, m is the number of estimated parameters, and s2a is the
biased residual variance.

Schwarz Bayesian Criterion (SBC)

(A6)

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

0

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 paretheses below the equations.

Model

        Parameter estimates and standard errors

Univariate

        $(1 - 0.538B - 0.505B5 + 0.369B6)\ddot{O}Yt = 1.209 + at$

        (0.107) (0.111) (0.122) (0.107)

One intervention

(1979)

        $(1 - 0.299B - 0.499B5 + 0.253B6)\ddot{O}Yt = 1.468 + at + 2.036It1979$

        (0.121) (0.109) (0.131) (0.105) (0.415)

Two interventions

(1949, 1979)

        $(1 + 0.305B3 - 0.377B5 + 0.225B6)\ddot{O}Yt = 4.206 + at - 0.754It1949 + 2.192It1979$

        (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, s^2a = 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	s^2a	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 paretheses 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)

$(1-0.572B)\ln Y_t = 0.655 + a_t + 0.917I_t1980$

(0.102) (0.040) (0.188)

Two interventions

(1950, 1980)

$(1-0.310B)\ln Y_t = 1.197 + a_t - 0.409I_t1950 + 1.145I_t1980$

(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, s^2_a = 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	s^2_a	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
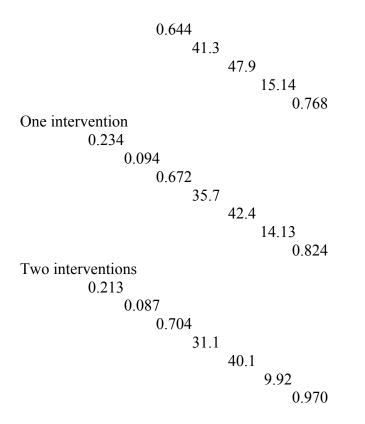   9.92
                0.970

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 paretheses 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)

$$\ln Y_t = 3.284 + a_t - 1.032 I_{t1948} + 1.005 I_{t1978}$$

(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, s^2_a = 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	s^2_a	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 paretheses below the equations.

Model

Parameter estimates and standard errors

Univariate

$(1 - 0.482B)\ddot{O}Y_t = 2.238 + (1 + 0.566B^2)a_t$

(0.110) (0.178) (0.117)

One intervention

(1978)

$(1 - 0.252B)\ddot{O}\ Y_t = 2.893 + (1 + 0.362B^2 a_t + 2.089I_t 1978$

(0.128) (0.163) (0.135) (0.433)

Two interventions

(1948, 1978)

$\ddot{O}\ Y_t = 4.377 + (1 + 0.241B^2 a_t - 0.946I_t 1948 + 2.675I_t 1978$

(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, s^2_a = 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

s^2_a

r²
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
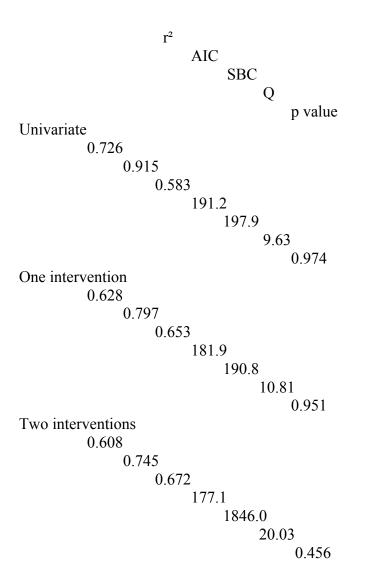0.745
0.672
177.1
1846.0
20.03
0.456

Figure captions

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.

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.

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.

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.

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.