Ephemeral Relationships in Salmon Forecasting: a Cautionary Tale

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Abstract

The influence of climate on marine populations is important for predicting stock abundance of marine fishes, and has led to increasing interest in environment-based forecasts (EBFs) for harvest management. While some climate indices have proven useful for explaining fluctuations in Pacific salmon stock abundance, there have also been sudden failures of EBF models. I analyzed temporal patterns in prediction skill for a variety of climate and ecosystem indicators as predictors of marine survival for a coastal coho salmon stock by computing prediction skill for 29 climate and ecosystem indices across multiple time scales to explore patterns of skill across time. Results demonstrate that predictive skill of EBF models is often ephemeral, arising and falling suddenly across time. This behavior can be explained both on a statistical basis and as a consequence of complex interactions between climate, ecosystems, and populations involving both climate regime shifts and ecosystem phase transitions. Forecast failures are problematic for traditional forecast-dependent harvest management approaches. Solutions for this problem may include improved forecast models and improved climate and ecosystem indicators, but developing management systems that are robust to forecast uncertainty would provide a more reliable response to expected rapid ecosystem changes in response to climate.

Keywords

climate, environment-based forecasts, salmon, Northeast Pacific, prediction, fishery management

1 Introduction

I begin with some remarks regarding Bill Peterson's role in this work. I had an office two doors down from Bill for 20 years, and enjoyed many hallway conversations about the role of biological oceanography in understanding and forecasting salmon population dynamics. Bill and I had common roots in field-based ecology, but my career had shifted toward quantitative analysis (population dynamics, ecosystem modeling, and ecological statistics), and we had perhaps more arguments than we should have about correlation, causation, and how to reliably identify relationships from ecological time series. This manuscript arose from discussions of the relevance of short (10-15 year) biological time series for forecasting salmon abundance and the stability of relationships in environment-based forecasts (EBFs). Two key questions here are first, whether predictive relationships between environmental indicators and salmon populations are stable through time, and second, how long a data series is necessary to provide reliable forecasts. To this purpose, I present an analysis of temporal patterns in prediction skill for a variety of climate and ecosystem indicators as predictors of marine survival for a coastal coho salmon stock. The intent of this work is neither to provide a good forecast nor to select the best indicators to use in a forecast, but rather to explore the problems of selecting indicators to use in EBFs, with a focus on patterns of forecast skill across time.

1.1 Environment-Based Forecasts for Pacific Salmon

The influence of climate (both short-term fluctuations and long-term trends) on marine populations is important for predicting stock abundance of marine fishes (Brander 2015), and the recognition of this issue has led to increasing interest in applying ecosystem indicators in harvest management (e.g., Cury and Christensen 2005; Jennings 2005). While long-term regional and local physical climate indices have proven useful for explaining fluctuations in Pacific salmon stock abundance (Scarnecchia 1981; Nickelson 1986; Holtby and Scrivener 1989; Beamish and Bouillon 1993; Hare and Francis 1995; Mantua et al. 1997; Pearcy 1997; Anderson 2000; Cole 2000; Botsford and Lawrence 2002; Koslow et al. 2002; Logerwell et al. 2003; Lawson et al. 2004; Scheuerell and Williams 2005; Rupp et al. 2011; Burke et al. 2013; Malick et al. 2015; McCormick & Falcy 2015), there have been few opportunities to examine the long-term stability of relationships among ecological indicators and fish populations. Recent measurements of biological ecosystem properties show strong short-term relationships with salmon marine survival (Peterson et al. 2006; Peterson et al. 2014), but it is unclear how stable these relationships will be across different climate regimes and ecosystem phases.

It has long been recognized among quantitative scientists that fish population dynamics are controlled by non-stationary properties arising from shifts in biological, physical climate, and management processes (Walters 1987). Climate-driven regime shifts were first recognized as an issue for Pacific salmon in the 1990s (Francis & Hare 1994; Hare & Francis 1995; Beamish et al. 1998) and more recent work has led to more detailed understanding of processes and methods for recognizing regime shifts (Peterson & Schwing 2003; Schwing et al. 2003; Overland et al. 2008; Irvine & Fukuwaka 2011; Sydeman et al. 2013). Similarly, there has been a recent explosion in literature related to ecosystem phase shifts in marine systems, due either to biological complexity or to physical forcing (Duffy-Anderson et al. 2005; Daskalov et al. 2007; Scheffer et al. 2009; Litzow et al. 2019). Beginning in the 1990s, technology has allowed increased attention to the relationships between climate processes and marine ecosystems at global and regional scales. For the North Pacific, this led to the development of regional ocean climate indicators including the Pacific Decadal Oscillation (PDO – Mantua et al. 1997), and later the North Pacific Gyre Oscillation (NPGO – Di Lorenzo et al. 2008).

Despite this knowledge base, non-stationarity has rarely been been incorporated into predictive models for salmon. The only instance of explicit recognition of regime shifts in a salmon management forecast is that for Oregon Coast Coho Salmon, where in 2009 an environment-based forecast model was retrospectively modified to incorporate an indicator variable to account for the 1977 regime shift (PFMC 2010); this model worked well for a short time, but begs the question of how future regime shifts could be accounted for in forecasts (Rupp et al. 2011). Other models have incorporated regime shifts implicitly by using decadal-scale climate indicators (especially the PDO) as proxies for regime shifts, but these models have also suffered from non-stationarity in the relationship between these proxies and salmon production, perhaps related to changes in coupling of variables in the climate system (Kilduff et al 2015, Joh & Di Lorenzo 2017).

1.2 History of Coho Salmon Forecasts

Salmon EBFs have a long history, and an only slightly shorter history of failures. Initially, salmon management forecasts were based strictly on stock-recruit relationships (e.g., Ricker 1954). The relationship between coho salmon and ocean conditions began to be recognized in the 1970s, starting with wind-driven upwelling (Gunsolus 1978; Scarnecchia 1981; Nickelson 1983). Shortly thereafter, this predictive relationship broke down, leading to the addition of ocean temperature as a covariate (Nickelson 1986). This relationship with upwelling and ocean temperature was adopted by the Pacific Fishery Management Council (PFMC) for coho salmon stock forecasts starting in 1994, with decreasing explanatory value until the model was abandoned in 2008, then resurrected in 2009, but with the addition of an artificial “regime index” to account for the model’s lack of fit during the 1990s (history summarized by Rupp et al. 2011). In the interim, a number of different EBF models were proposed, notably a multivariate model based on four ocean indicators (Logerwell et al. 2003), one based on freshwater indicators (Lawson et al. 2004), and most recently a multivariate ensemble predictor using a wide variety of indicators (Rupp et al. 2011). The last model was adopted by PFMC in 2011 for forecasting Oregon Coast naturally-produced coho salmon, with somewhat mixed results (PFMC 2019, Table III-1).

1.3 Salmon Harvest Management

To understand the role of forecasts in harvest management, a brief introduction to the harvest management process is necessary. Along the west coast of North America, salmon are commercially harvested from central California north through the Bering Sea, with much national, regional, and stock-specific variation in the details of management. However, the basic process is similar in all regions: long-term escapement goals are set by regional management bodies as a balance of economic return and conservation considerations, then an annual management cycle sets annual harvest limits for mixed-stock ocean fisheries and terminal (bay and river) fisheries. The typical annual cycle proceeds in a number of steps (e.g., PFMC 2012): 1) A pre-season recruitment forecast is prepared; 2) from this, annual catch limits are set based on optimum yield considerations incorporating harvest and conservation goals and current data on stock abundance and condition; 3) fishing limits (combinations of season and area openings and other stock-specific regulations) are established; 4) for some stocks, in-season monitoring is conducted and forecasts updated, leading to revised fishing limits. Recruitment forecasts are central to this process, and are conducted with a variety of statistical models, including stock-recruit models, sibling regressions (predicting older age group abundance based on previous returns of younger age groups in the same cohort), environmental indicator regressions, or combinations of the above (e.g., PFMC 2019).

1.4 Example: Coastal Coho Salmon

To illustrate some of the problems encountered in salmon EBFs, I chose to analyze predictions for a single example coho salmon stock: the Oregon Production Index hatchery-produced (OPIH) stock, which includes hatchery-produced coho salmon primarily from the Columbia River and Oregon coast (PFMC 2019). This stock was chosen for two reasons: it has a simple age-structure, with adults returning primarily at age 3, and it is composed of hatchery fish with smolts released near the time of ocean entry. These two characteristics simplify the analysis in that variability in freshwater rearing is virtually eliminated, meaning that ocean-related factors should be the main drivers of variation in returns. It is also an important stock for commercial harvest, and not of conservation concern other than through its effects on other stocks.

The life-cycle of these fish begins with spawning in the winter (year one), then hatchery rearing for about 1-1/2 years after which pre-smolts are released and migrate to the ocean in spring of year two, feeding migration in the ocean from summer of year two to autumn of year three, then a return migration to their natal hatchery. (A small proportion of males returns to freshwater in year 2, these have been ignored in this analysis.) Ocean harvest targets returning adults in the summer and fall of year three. Thus, the life cycle is split about evenly between freshwater and ocean phases. Most ocean mortality (and its variation) is believed to occur in the first several months of ocean life (Pearcy 1992), so ocean-related environmental indicators used here are for the calendar year of ocean entry.

2 Methods

The analysis consists of computing the forecast skill of log-linear regression models for OPIH coho salmon marine survival as functions of various climate and ecosystem indicators at a variety of time scales, then assessing temporal patterns in the skill for each regressor. Complete data sets and R-language (R Development Core Team 2013) scripts to update the data and reproduce the analysis are available on GitHub at https://github.com/tcwain/EphemeralRelationships.

2.1 Data

Data used consists of publicly-available time series of coho salmon abundance, climate indicators (at both North Pacific basin scale and local coastal scale) and biological ecosystem indicators mainly from the Newport Hydrographic (NH) Line. Data series, abbreviations, and sources are summarized in Table 1.

2.1.1 Marine survival

A marine survival index (Figure 1) was computed for each cohort of OPIH coho salmon based on data for total hatchery smolt releases for all stocks in the OPI area and estimated total pre-harvest adult recruitment for those stocks. Reliable data for this calculation is available from 1960 to 2018 (McGie 1984; PFMC 2004; PFMC 2019). The calculation is:

$$Survival_t = \frac{Recruits_{t+1}}{Smolts_t},$$

where *t* is the year of ocean entry. Because hatchery salmon are released in-river before smolting, this ratio includes some river and estuarine mortality, and is thus only an approximate index of actual marine survival.

2.1.2 Climate and ecosystem indicators

I used a number of short- and long-term environmental indices (Table 1) to predict marine survival of OPI hatchery coho salmon. These included three types of data: regional physical indices, local physical indices, and biological ecosystem indicators. All data used was indexed to the year of ocean entry (smolt year) of the OPIH coho salmon cohorts, one year prior to the return year for the cohort. A wide set of indicators have been used in salmon forecasting (Rupp et al. 2011; Burke et al. 2013; Peterson and Burke 2013), and from these I selected a number of indicators that were commonly used and showed some promise in forecasting. At the ocean basin scale, these were the PDO (Mantua et al. 1997), NPGO (Di Lorenzo et al. 2008), and the Oceanic Niño Index (ONI – Kousky and Higgins 2007). At the local scale, series include both long-term climate indicators – coastal water temperature at Charleston, Oregon (CWT), coastal upwelling index at 45°N (UWI – Bakun 1973) and upwelling spring transition (Logerwell et al. 2003) – and shorter series of ecosystem indicators derived from the Newport Hydrographic Line studies initiated by Bill Peterson (Peterson et al. 2014). Most of the long-term climate indicators were obtained at monthly or finer time periods. For the analysis, these series were transformed into 3-month seasonal averages representing winter (Jan-Feb-Mar), spring (Apr-May-Jun), summer (Jul-Aug-Sep), and autumn (Oct-Nov-Dec). In addition to spatial scale, these indicators vary in temporal scale as well, with some (e.g., PDO, NPGO) reflecting decadal-scale climate processes, while others (e.g., ONI, UWI, CWT) reflect short seasonal to annual scale processes. Thus, different indicators should be expected to correlate to different scales of variability in population dynamics.

2.2 Statistical Methods

The analysis consisted of fitting univariate linear regression models predicting log-transformed OPIH coho salmon marine survival as a function of an individual climate or ecosystem indicator at different time scales. Log-transformations are commonly used for population and survival data (e.g., Kimura 1988; Koslow et al. 2002) both to stabilize variances and to better represent the multiplicative nature of survival processes. If survivals are relatively high, this can risk predictions of survival exceeding 1.0, but here the maximum observed survival was less than 12% (Figure 1) and the predictions calculated never exceeded 1.0. For a data series of length *N*, the regression was computed for all overlapping time intervals (moving windows) of length *n* (the time scale), where *n* ran from a lower limit of 5 years to the full series length (*N*); for each time scale *n*, this resulted in a time series of *N*-*n*+1 regression fits. This procedure was repeated for each of the 29 seasonal and annual indicator series in Table 1. Each regression was summarized by a goodness-of-fit statistic and the regression slope.

There are a number of means of measuring goodness-of-fit for statistical models, including residual error, various information criteria, and a number of forms of cross-validation. Here, I use the model skill, which is a relative measure defined as 1 – (prediction error) / (reference error) (American Meteorological Society 2019). In particular, I used a skill measure based on “leave-one-out” cross-validation (LOO CV – Borra and Di Ciaccio 2010; Rupp et al. 2011):

$$S_{LOO} = 1 - \frac{(n-1)\sum\left(\hat{Y}_{(i)} - Y_i\right)^2}{(n-2)\sum(\bar{Y} - Y_i)^2}$$

where the sums are over the n data points and $\hat{Y}_{(i)}$ is the logarithmic-scale predicted value of Y_i from the model with point i left out. The value of this statistic ranges from 1.0 for perfect model fit, through 0.0 when the model predicts the data mean exactly, to negative values when the fit is worse than the data mean. In the results here, negative values have been truncated to 0.0 to simplify visual display; any model with skill <= 0.0 is essentially useless as a predictor. Borra and Di Ciaccio (2010) note that LOO CV is not the best measure for model selection, but that does not matter in this application.

Finally, the full set of predictions at all time scales for each indicator were visually summarized in a “dot” or “bubble” plot with dots proportional to model skill and color-coded to the slope of the regression relationship. These diagrams provide a detailed tool for diagnosing non-stationarities in the relationships.

As mentioned, a wide variety of EBF models have been used to forecast salmon and other resources, including linear, quasi-linear and non-linear univariate and multivariate approaches. I have chosen univariate linear models here because they are computationally fast and easy to understand. I do not advocate using such simplistic models for forecasting, and use them here only to illustrate a general problem. Multivariate and non-linear regression models also suffer from the same problems and will also exhibit ephemeral results, but are more difficult to analyze.

3 Results

The full analysis (all scales across all years) illustrates a wide variety of patterns in predictive skill (Supplemental Figures S-1 – S-8). Using the PDO as an example (Figure 2), one sees first the strong seasonal pattern, with spring (AMJ) and summer (JAS) seasonal means having moderate to strong skill across many years, while autumn (OND) means have moderate to strong skill only before 1994 and winter (JFM) means have only scattered years with moderate to strong skill, primarily at only short time scales. Next, there are sudden temporal breaks in skill. Notably, the summer and autumn indices have the highest skill for the years 1975 to 1993, then negligible (autumn) or only moderate (summer) skill after that; in contrast, the spring PDO had strong skill with a positive slope in the early 1970s, then negligible skill until the mid-1980s, and increasing skill with a negative slope after that. Finally, there are patterns of skill with time scale (interval length). Not surprisingly, at short time scales there are scattered short periods of high skill when short term fluctuations in the two data sets happen to align. Perhaps more interesting are the diagonal swaths of strong skill that begin abruptly and are carried forward through time, such as the fall PDO pattern beginning in 1975 at short (5 to 8 y) scales and continuing until 1993, or the spring pattern beginning around 2000 at short (7 to 12 y) scales and continuing through at least 2018. These suggest a short-term predictable pattern in the data that arises suddenly and raises the skill for a number of years.

To compare patterns across indicators, it is easier to focus on results for indicators at a few time scales. Results are presented at two time scales. First is the variable scale used in practical forecasts, where models are fitted to all prior data, then updated each year as management forecasts are made. This scale corresponds to points along the uppermost diagonal in the full-analysis figures (S-1 – S-8). Results at this scale (Figure 3) show a mix of strong and weak relationships varying through time, with strong relationships lasting for spans ranging from less than 5 years (e.g., winter PDO and spring and summer UWI) to more than 20 years (e.g., spring and summer PDO, Logerwell spring transition and winter coastal water temperature), but none lasting through the entire data series. Second, I present results at a fixed time scale, focusing on a relatively short 15-year scale that might be used to evaluate newly-available data series. At this scale (Figure 4), there are fewer substantial relationships but these tend to have higher skill than those using all prior data and tend to last for less than 20 years.

4 Discussion

4.1 Ephemeral Relationships

When predictive skill of the regression models is viewed across time (Figures 3 and 4), perhaps the most striking feature is that for any predictor, skill can arise suddenly and can disappear suddenly. This means that the predictive relationships are ephemeral, rising and falling with changing conditions. (Such relationships are variously described as "ephemeral", "transient" or "mirage" relationships in the literature – Ye et al. 2015.) These patterns are often synchronous across multiple predictors, as with the strengthening of skill in the early 1990s for spring PDO, coastal water temperature, NPGO, and Logerwell spring transition, or the sudden loss of skill in 2011 for biological indicators and NPGO (Figure 3); this is in part a consequence of the strong correlations among several of the indicators (e.g., Logerwell et al. 2003; Rupp et al. 2011), but also due to patterns in the survival time series (see Section 4.1.1). The ephemeral nature of some of these relationships has led to the history of abandoned forecast models for coastal coho salmon (Sect. 1.2), resulting in suboptimal harvest management for the years of transition between models.

4.1.1 Statistical Mechanisms

These sudden synchronous changes in skill have an obvious methodological explanation: abrupt changes in the distribution of the marine survival series that do or do not have corresponding changes in predictor time series. Examining the survival time series (Figure 1), the series is fairly stable in the 1960s to middle 1970s, when a decline sets in and continues through the early 1980s. This is followed by a period of short-term variability that is ended by an abrupt decline in 1990 to previously unobserved levels, which in turn is ended by an abrupt rise in survival in the late 1990s. Subsequently, there is another period of relative stability up until 2010, when there is a brief period of very high variability followed by a decline to relatively low survival at the end of the data. This is a richly-patterned time series, and none of the individual predictors examined here capture all these patterns.

One can understand the problem by looking in detail at the predictor that performs the best (spring PDO) with a related one that captures only part of the pattern (autumn PDO). These are overplotted on the survival time series in Figure 5. Prior to 1980, there was limited variation in survival around a fairly constant mean, and neither seasonal PDO series had any skill in predicting these short-term fluctuations (Figure 3). (This should be expected, as the PDO reflects decadal-scale fluctuations.) Both series did capture the decline in survival around 1980 (the biggest signal in the series up to that time) and both retained moderate predictive skill until the next big change. The extremely low survivals of the middle 1990s provide the strongest signal in the entire survival time series, so no predictor that did not reflect that event could have strong skill subsequently. Spring PDO does reflect that event and autumn PDO does not; thus, one exhibits high skill for the remainder of the data series, and the other has essentially no skill after

1993. Similarly, Charleston water temperature, NPGO, and Logerwell spring transition all reflected this 1990s pattern to varying degrees, and all have moderate skill during and subsequent to the 1990s.

4.1.2 Ecological explanations

The discussion above (Section 4.1.1) only relates to the mechanistic (statistical) explanations for indicator performance, and does not explain predictor performance in terms of causality, nor their predictive value in terms of likely future performance. There are a number of complications that could contribute to sudden changes in predictive relationships: complexity of the climate system, manifested as climate regime shifts, complexity of ecosystems, particularly in the form of ecosystem phase transitions, and complexity of the salmon life cycle.

Climate regime shifts affecting fish populations have been identified throughout recent history (e.g., Francis and Hare 1994; Mantua et al. 1997). Three regime shifts in the north Pacific have been identified within the span of the OPIH coho data, in about 1976, 1989, and 1998 (Hare and Mantua 2000; Overland et al. 2008; Beaugrand et al. 2015), and these have been related to changes in Pacific salmon abundance, with different effects depending on species and region (Hare and Francis 1995; Beamish et al. 1998; Irvine and Fukuwaka 2011). While these shifts correlate with changes in abundance or productivity in many salmon stocks, there is no convincing evidence that shifts in multiple physical drivers would change the relationships between populations and those drivers, unless the effect is mediated through some associated change in ecosystem structure.

Complexities in ecosystems can lead to strongly non-linear dynamics of component populations, resulting in multiple stable states (phases) and potentially chaotic responses (Turchin and Taylor 1992; Polis and Strong 1996). Duffy-Anderson et al. (2005) noted the interactions of climate, ecosystem structure, and fisheries in determining fish recruitment phase transitions, which may be initiated by climate regime shifts, but also can disrupt any relationship between recruitment and physical drivers. Thus, one might expect that in complex systems, simple relationships between drivers and recruitment would change over time, arising and falling as ecosystems restructure.

Finally, the salmon life-cycle itself with short generations and strongly age-structured populations leads to complex population dynamics (Caswell et al. 1984; Worden et al. 2010). In particular, cohort resonance can either enhance or disrupt the response of populations to environmental drivers (Bjørnstad et al. 2004; Worden et al. 2010; Botsford et al. 2014). This in itself could cause apparent regression relationships between drivers and fish populations to appear and disappear through time.

4.2 Solutions

Past approaches to EBFs, which sometimes amount to “fishing expeditions” for climate indicators to predict marine resources, not only don’t work, but produce results that mislead by yielding seemingly good predictive power that doesn’t hold up. In part, this can be attributed to poorly understood or poorly implemented statistical approaches for climate time series (von Storch 1999; DelSole and Shukla 2009; Ambaum 2010), but is also inherent in the complex dynamics of climate-driven ecosystems that may render accurate prediction of individual species impossible (Roessig et al. 2004; Perry and McKinnell 2005). As we move into an era of more rapid physical and ecological changes, new techniques will be required. These must consider the transitory nature of short-term relationships that result from regime shifts and ecosystem phase transitions. Solutions might include developing better forecast models, identifying better indicators, and improving the harvest management system itself.

4.2.1 Better models?

The simple single-factor regression EBF models used as an example here are no longer used in management forecasts – many improved approaches to forecasting have been tried over the past two decades. There are examples of multivariate linear or quasi-linear regression models (Logerwell et al. 2003), multivariate principal component and maximum covariance regression models (Burke et al. 2013), mixed stock-recruit-environment models (Haeseker et al. 2005; Haeseker et al. 2008), dynamic linear models (Scheuerell and Williams 2005), multi-model ensembles (Rupp et al. 2011), probabilistic networks (Malick et al. 2015), and empirical dynamic modeling (Ye et al. 2015). These and other approaches have been reviewed by Megrey et al. (2005) and McCormick and Falcy (2015). While many of these approaches do incorporate better methods for dealing with multivariate complexity in relationships, most do nothing to solve the problem of ephemeral relationships – so long as they are fitted with constant parameters to limited past data, they will still fail when causal effects shift. The possible exceptions are the dynamic models, which can explicitly incorporate statistical non-stationarity, allowing change in parameters and potentially change in importance of different environmental indicators through time. However, for multivariate models they are difficult to fit and have large parameter space, so will generally have low forecast precision. It remains to be seen if this class of models can respond to rapid shifts in physical drivers or ecosystem phases.

4.2.2 Better indicators?

Many promising environmental indicators for salmon have failed the test of time, often because they seem to be "one-trick ponies" that do well at predicting one period of population variation, but fail when a different pattern of variation emerges (Sect. 4.1.1). Of the indicators examined here, only the spring and summer PDO retained skill across multiple regime shifts, and even those series did not perform well for OPIH coho during the 1970s regime shift (although the PDO did correlate with changes for Alaska salmon for that period – Mantua et al. 1997).

Indicator selection could be improved by a number of means. A primary goal should be to avoid the common statistical pitfalls that lead to overconfidence in predictive performance, including issues of serial correlation, multicolinearity, and short data series (e.g., von Storch 1999; DelSole and Shukla 2009). Multicolinearity can be addressed via standard multivariate statistical techniques and advanced multivariate regression techniques (Methratta and Link 2006; Burke et al. 2013). Van de Pol et al. (2016) suggest a systematic process for indicator selection that includes optimizing the time window for weather indicators relative to ecological responses. Still, improved statistical selection of indicators will not overcome the problem of ephemeral relationships, although this can be reduced by using only variables with a sufficiently long history to represent multiple climate regime shifts and/or ecosystem phase transitions.

4.2.3 Better management?

Improved models and improved indicators can only go so far in reducing prediction error, and are unlikely to completely prevent the sudden prediction failures that characterize salmon management. The best strategy would be to devise management systems that can deal with the uncertainties inherent in EBFs. A first step would be to evaluate the effects of forecast uncertainty on alternative management protocols through management strategy evaluations to ensure that forecasts have sufficient skill to support decision-making and that they actually improve management outcomes (economic value and/or conservation values) (Kaje and Huppert 2007). Using such an approach, Rupp et al. (2012) determined that the current conservation-oriented management strategy for Oregon coast natural coho salmon is much more robust to forecast errors than a traditional constant-escapement strategy. Another approach would be more wide-spread adoption of in-season forecast updates and adjustments to harvest levels. This method is used in a number of terminal and near-terminal salmon fisheries (notably for Bristol Bay Sockeye Salmon, Fraser River Sockeye Salmon and Columbia River Chinook Salmon), and, if well-implemented, can reduce the effects of poor pre-season forecasts (e.g., Holt and Peterman 2008; Dorner et al. 2009).

Beyond such technical fixes, entirely different management strategies may need to be considered that embrace, rather than suffer from, the uncertainties inherent in complex systems. As one study put it: “Once we free ourselves from the illusion that science or technology (if lavishly funded) can provide a solution to resource or conservation problems, appropriate action becomes possible” (Ludwig et al. 1993). Their list of strategies includes both robustness and active adaptive management: favor actions that are robust to uncertainties, favor actions that are informative, probe and experiment, and favor actions that are reversible. If such robust strategies were to be adopted, it is possible that forecasting would not be important at all (Walters 1984).

Over recent decades, there has been a shift in management focus for salmon from optimizing harvest (economic efficiency) to conservation management (protecting species and stocks at risk) and ecosystem services (leaving “surplus” for other benefits such as stream nutrients and providing food for orcas). So far, this has been accomplished by tweaking the traditional management models, or even by creating management exceptions for protected stocks. Perhaps it is time to abandon management systems dating from the time before the death of MSY (Larkin 1977) and build new robust management management policies that embrace uncertainty and surprise in a balanced context of economic return and ecosystem conservation in the face of climate change.

4.3 Conclusions

Predictive skill of EBF models can be ephemeral, arising and falling suddenly across time, and these patterns are often synchronous across multiple predictors. This behavior is an expected consequence of complex interactions between climate, ecosystems, and populations involving both climate regime shifts and ecosystem phase transitions. Forecast failures are problematic for traditional forecast-dependent harvest management approaches, and failures are inherent to traditional regression approaches when applied to complex dynamic systems. Solutions of this problem may include improved forecast models and improved climate and ecosystem indicators, but these improvements are unlikely to effectively account for climate and ecosystem shifts.

Developing management systems that are robust to forecast uncertainty would provide a more certain response to expected rapid ecosystem changes in response to climate.

Bill Peterson and others pursued using biological indicators of lower trophic production as predictors of salmon growth and survival (Peterson et al. 2006; Brodeur et al. 2008; Peterson et al. 2011; Ruzicka et al. 2011; Daly et al. 2013). These indicators showed early promise as explanatory variables, but these predictive relationships failed in the last decade. This highlights the nature of predictive relationships in complex systems: even when predictors have a probable causal mechanism related to population dynamics they may not perform well in forecasting. In a complex system there are always multiple, linked causal pathways that may shift in importance over time. Causality is neither necessary nor sufficient for good prediction (Walters 1984).

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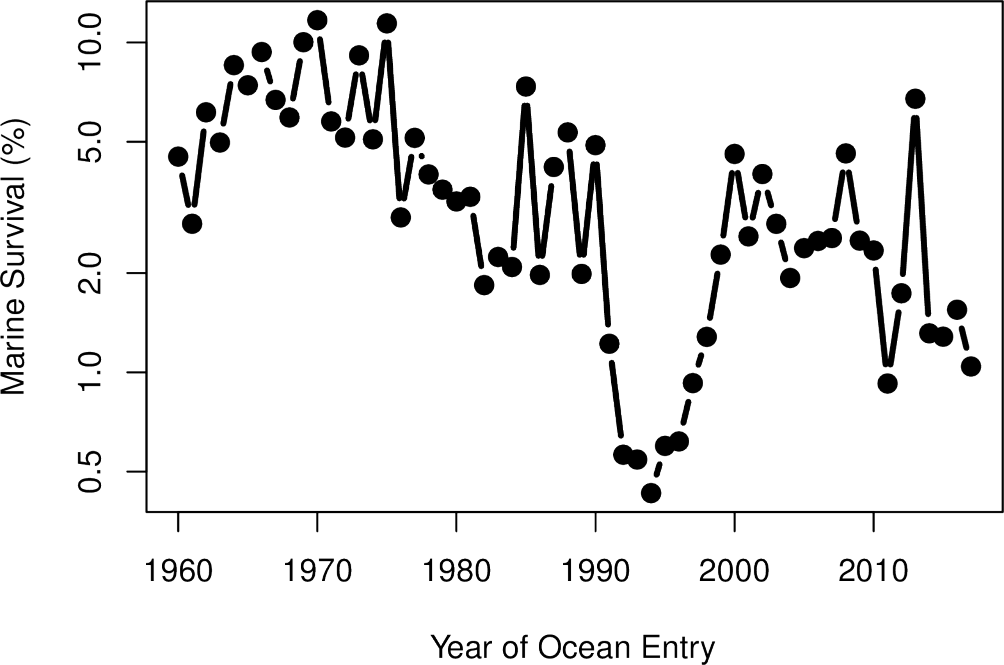
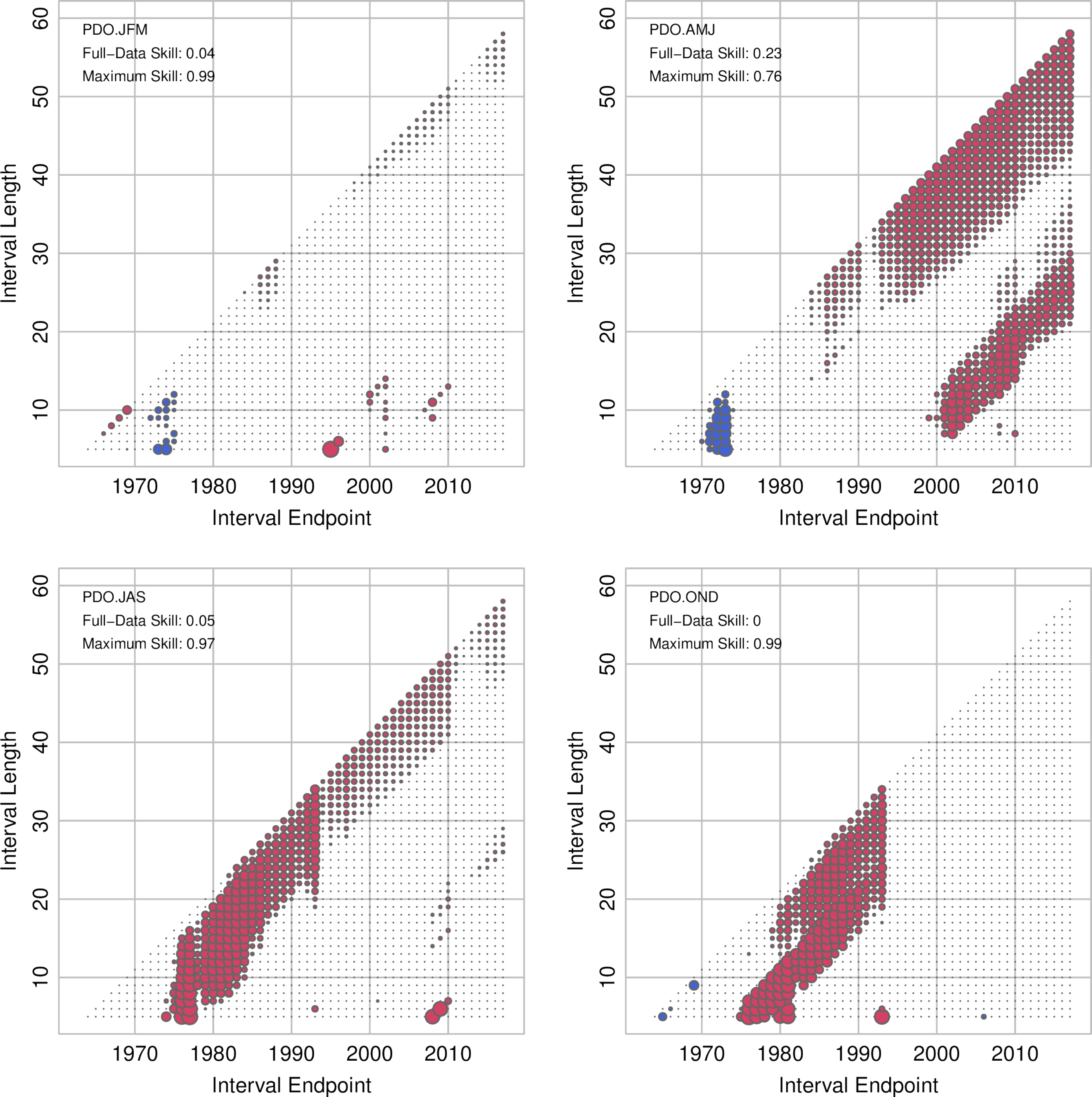
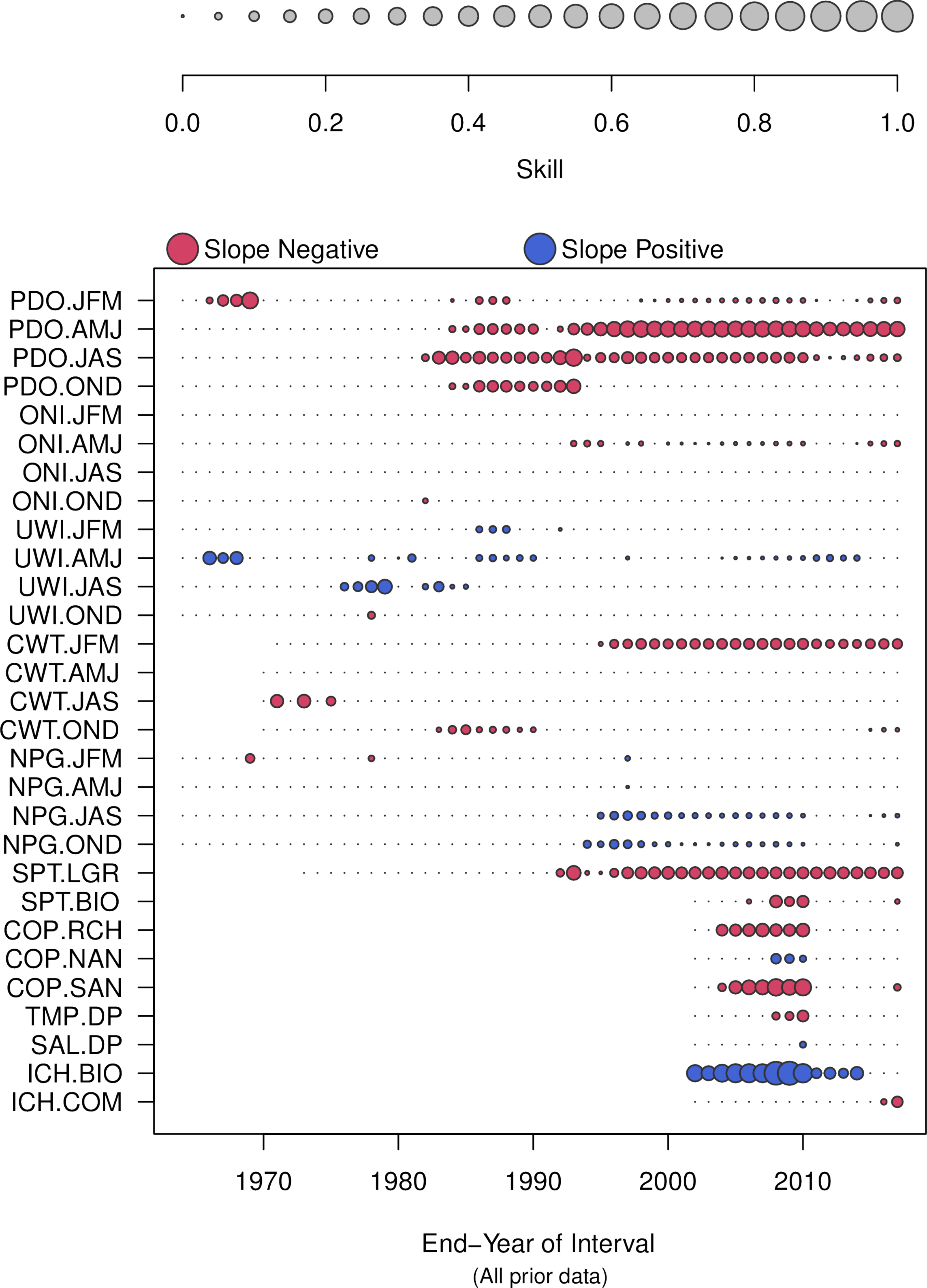
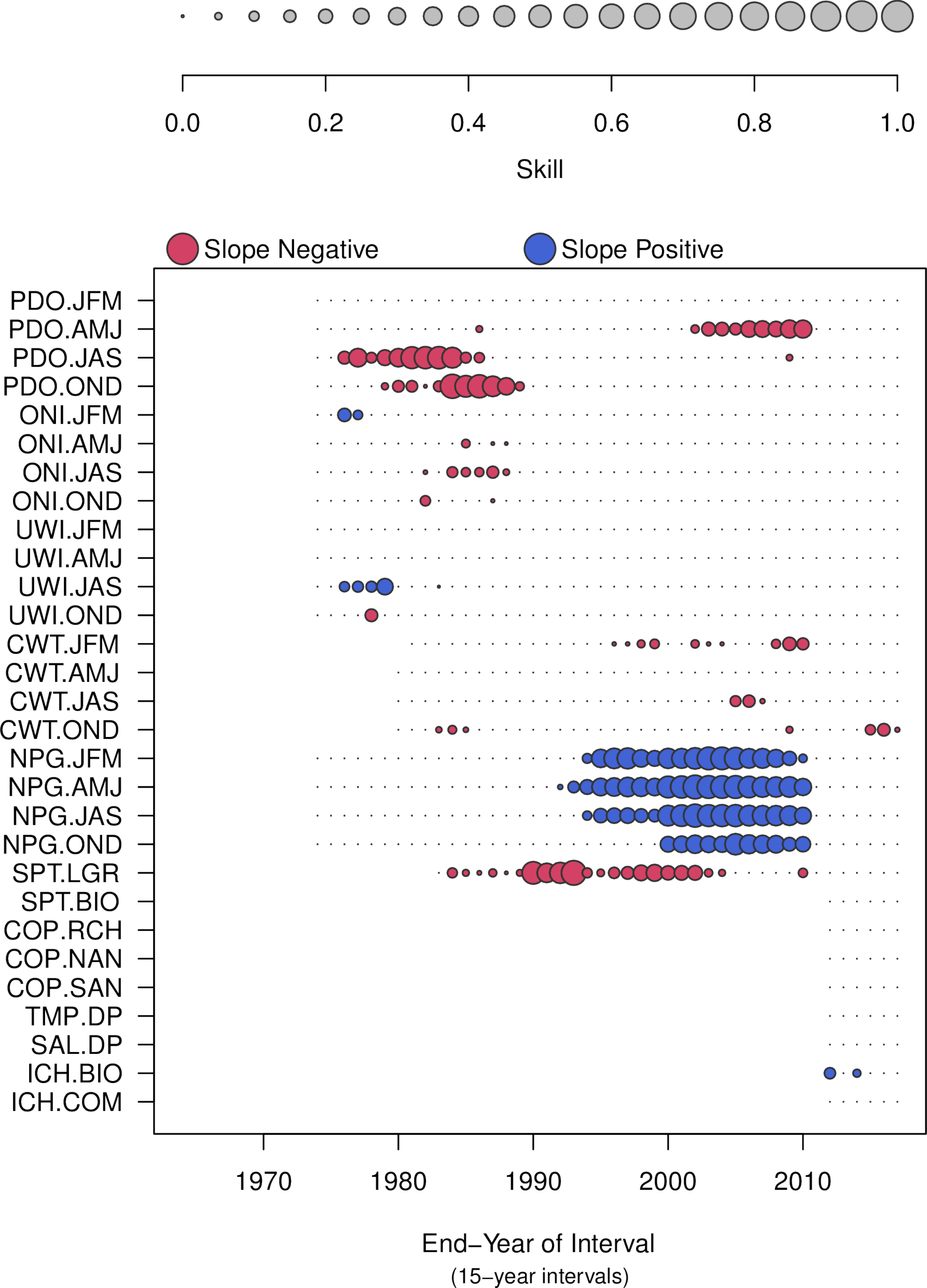

Marine Survival (%)
10.0
5.0
2.0
1.0
0.5
1960
1970
1980
1990
2000
2010
Year of Ocean Entry



PDO.JFM
Full−Data Skill: 0.04
Maximum Skill: 0.99
PDO.AMJ
Full−Data Skill: 0.23
Maximum Skill: 0.76
PDO.JAS
Full−Data Skill: 0.05
Maximum Skill: 0.97
PDO.OND
Full−Data Skill: 0
Maximum Skill: 0.99
Interval Length
Interval Endpoint
10
20
30
40
50
60
1970
1980
1990
2000
2010



0.0
0.2
0.4
0.6
0.8
1.0
Skill
Slope Negative
Slope Positive
PDO.JFM
PDO.AMJ
PDO.JAS
PDO.OND
ONI.JFM
ONI.AMJ
ONI.JAS
ONI.OND
UWI.JFM
UWI.AMJ
UWI.JAS
UWI.OND
CWT.JFM
CWT.AMJ
CWT.JAS
CWT.OND
NPG.JFM
NPG.AMJ
NPG.JAS
NPG.OND
SPT.LGR
SPT.BIO
COP.RCH
COP.NAN
COP.SAN
TMP.DP
SAL.DP
ICH.BIO
ICH.COM
1970
1980
1990
2000
2010
End−Year of Interval
(All prior data)


0.0
0.2
0.4
0.6
0.8
1.0
Skill
Slope Negative
Slope Positive
PDO.JFM
PDO.AMJ
PDO.JAS
PDO.OND
ONI.JFM
ONI.AMJ
ONI.JAS
ONI.OND
UWI.JFM
UWI.AMJ
UWI.JAS
UWI.OND
CWT.JFM
CWT.AMJ
CWT.JAS
CWT.OND
NPG.JFM
NPG.AMJ
NPG.JAS
NPG.OND
SPT.LGR
SPT.BIO
COP.RCH
COP.NAN
COP.SAN
TMP.DP
SAL.DP
ICH.BIO
ICH.COM
1970
1980
1990
2000
2010
End−Year of Interval
(15−year intervals)

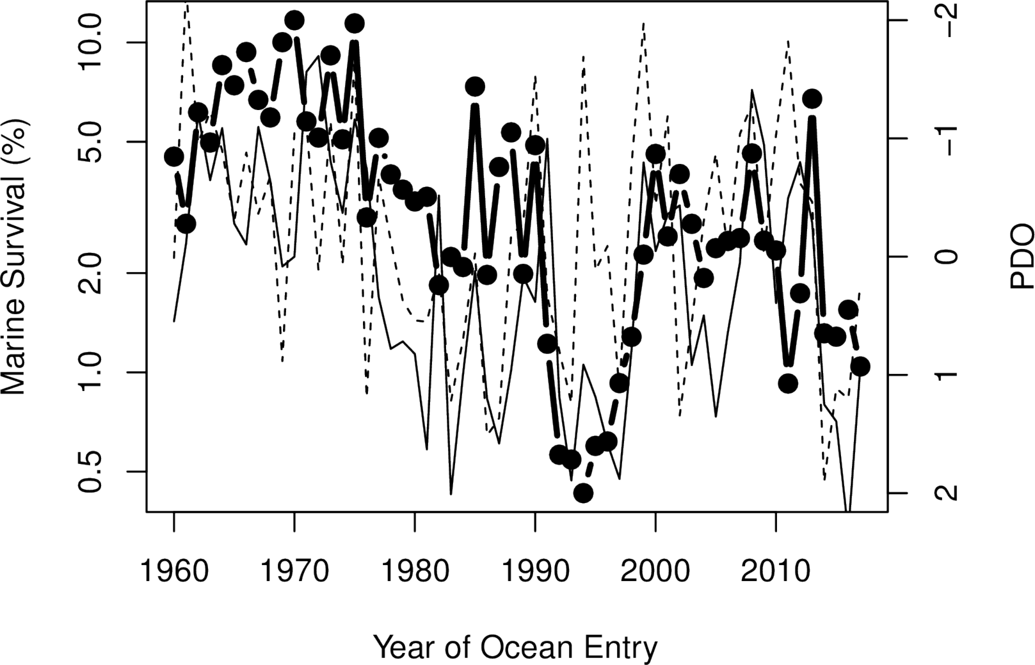

Marine Survival (%)
10.0
5.0
2.0
1.0
0.5
PDO
−2
−1
0
1
2
1960
1970
1980
1990
2000
2010
Year of Ocean Entry

Table for PROOCE_2019_180.

Table 1. Data series used in the analysis.

Data Series	***Abbreviation***	***Frequency***	***Years***	***Source***
		Salmon Survival		
Oregon Production Index Hatchery Coho Salmon Marine Survival Index	OPIH.SRV	Annual	1960-2018	Calculated using data from (McGie 1984; PFMC 2004; PFMC 2019)
		Regional Physics		
Pacific Decadal Oscillation	PDO.mmm*	Seasonal	1960-2018	(Mantua 2019)
Oceanic Niño Index	ONI.mmm	Seasonal	1960-2018	(Climate Prediction Center 2019)
North Pacific Gyre Oscillation	NPG.mmm	Seasonal	1960-2018	(Di Lorenzo 2019)
		Local Physics		
Coastal Water Temperature at Charleston, Oregon	CWT.mmm	Seasonal	1966-2018	Calculated using data from (National Oceanic and Atmospheric Administration 2019a; National Oceanic and Atmospheric Administration 2019b)
Upwelling Index, 45°N	UWI.mmm	Seasonal	1967-2018	(Pacific Fisheries Environmental Laboratory 2019)
Upwelling Spring Transition	SPT.LGR	Annual	1969-2018	(Logerwell et al. 2003; PFMC 2019)
Deep Temperature at Stonewall Bank (C, May-Sep average)	TMP.DP	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Deep Salinity at Stonewall Bank (psu, May-Sep average)	SAL.DP	Annual	1998-2018	(Northwest Fisheries Science Center, 2019)
		Ecosystem Indicators		
Copepod Richness Anomaly (no. species, May-Sep average)	COP.RCH	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Northern Copepod Anomaly (mg C m-3; May-Sept)	COP.NAN	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Southern Copepod Anomaly (mg C m-3; May-Sept)	COP.SAN	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Biological Spring Transition (day of year)	SPT.BIO	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Ichthyoplankton Biomass Index (Jan-Mar)	ICH.BIO	Annual	1998-2018	(Northwest Fisheries Science Center 2019)
Ichthyoplankton Community Composition Index (Jan-Mar)	ICH.COM	Annual	1998-2018	(Northwest Fisheries Science Center, 2019)

*'mmm' represents an abbreviation of the months included in the seasonal mean: 'JFM' for January-February-March, 'AMJ' for April-May-June, 'JAS' for July-August-September, and 'OND' for October-November-December.