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Attachment 3
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Forecast Models for Oregon Coastal Natural Coho Salmon (*Oncorhynchus kisutch*) Adult Recruitment

SUMMARY REPORT

29 September 2010

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ABSTRACT

Generalized additive models (GAMs) were used to investigate the relationships between annual recruitment of Oregon coastal natural coho salmon (*Oncorhynchus kisutch*) and indices of physical ocean environment conditions. Nine indices were examined, ranging from indices of large-scale ocean patterns (e.g., Pacific Decadal Oscillation (PDO)) to local ecosystem variables (e.g., coastal water temperature near Charleston, OR). GAMs with 2 and 3 predictor variables were evaluated using a set of performance metrics aimed at quantifying the models' skill at making short-lead (~1 year) forecasts. It was found that high explanatory power and promising forecast skill could be achieved when the spring/summer PDO averaged over the 4-years prior to the return year was used to explain the low-frequency (multi-year) pattern in recruitment while a second (or second and third) variable was used to account for year-to-year deviations from the low-frequency pattern. When averaging the predictions from a set of models (i.e., taking the ensemble mean) a higher skill (in terms of variance explained or a cross-validation score) was achieved than by selecting any single model. Making multiple forecasts from a set of models also provides a range of possible outcomes that reflects, to some degree, the uncertainty we have in our understanding of how salmon productivity is driven by physical ocean conditions.

INTRODUCTION

Past methods for forecasting adult recruitment of Oregon Coastal Natural (OCN) coho salmon have performed, overall, poorly during the previous decade. The last 10 years has seen a dramatic reversal in an approximately 25-year decline in recruitment, followed by yet another decline to previous lows in but 5 years, with the last 2 years showing once again a return to moderately-high abundances (see Fig. 1a). A consequence is that this apparent change in the recruitment pattern has invalidated, or weakened, the empirical relationships that make up the past forecast models.

In order to arrive at an improved forecasting method, we examined a suite of potential predictor variables that includes indices of both large-scale ocean conditions (Multi-variate ENSO index, North Pacific Gyre Oscillation index, North Pacific index, Ocean Niño index, and Pacific Decadal Oscillation index) and local ocean conditions (upwelling wind strength, upwelling spring transition, sea surface temperature and sea surface height). We built generalized additive models (GAMs) using various combinations of indices and evaluated the models in terms of their skill at making forecasts. We chose GAMs because they have the powerful attribute of not imposing *a priori* a given functional relationship between the predictor(s) and the predictand. GAMs have been used previously to explore relationships between environmental variables and marine survival of Oregon Production Index (OPI) hatchery coho (Logerwell *et al*., 2003) and freshwater survival of OCN coho (Lawson *et al*., 2004).

METHODOLOGY

Data

The OCN coho salmon stock is naturally produced in rivers and lakes along the Oregon coast south of the Columbia River. This stock aggregate is a component of the greater OPI area coho stock, which also includes hatchery and natural coho from the Columbia River and hatchery coho from the Oregon coast (though coastal hatchery coho have historically been a minor component of the OPI and are currently inconsequential).

Annual time series of aggregate OCN coho adult recruitment for the period 1970 – 2009 from Oregon coastal rivers (OCNR) and lakes (OCNL) were generated from spawner escapement estimates (Oregon Department of Fish and Wildlife) and fishery exploitation rates (Chapter 3 in Pacific Fishery Management Council, 2010). The river and lake data were kept separate because it is believed that population dynamics differ markedly between river and lake runs (Lawson *et al*., 2004). This report focuses exclusively on the river (OCNR) estimates.

We tested 9 ocean environment indices and parent spawner abundance as predictor variables for ONCR recruitment. The 9 indices are listed in Table 1. A description of each index and a more detailed rationale behind their selection is given in the full report. In general, these indices were chosen because previous studies have found them to be correlated to survival and recruitment of salmon in the Pacific Northwest (PNW).

Three-month running means were calculated for each environmental variable with the exception of MEI which was left as a 2-month running mean (the condition in which it was obtained). The following format was used to label each environmental variable: **VVV.MMM,** where VVV is the 3-character abbreviation of the environmental variable, and MMM are the months over which the mean of variable is calculated.

Table 1. Potential predictor variables

Predictor variable	Short name	Hypothesis
Multivariate ENSO Index	MEI	High value -> low recruitment
North Pacific Gyre Oscillation	NPGO	High value -> high recruitment
North Pacific Index	NPI	High value -> high recruitment
Ocean El Niño Index	ONI	High value -> low recruitment
Pacific Decadal Oscillation	PDO	High value -> low recruitment
Day of Spring Transition of Upwelling Period	SPR	High value -> low recruitment
Sea Surface Height at Newport, OR	SSH	High value -> low recruitment
Sea Surface Temperatures near Charleston, OR	SST	High value -> low recruitment
Coastal Upwelling Index (45^{o} N)	UWI	High value -> high recruitment
Parent Spawner Abundance	$N_{spawners}$	High value -> high recruitment

General Additive Models (GAMs)

We used generalized additive models (GAMs) to build relationships between environment indices and OCNR recruitment. A GAM with, for example, 3 predictor variables, can be expressed in the following general form:

$$\hat{Y} = f(X_1) + f(X_2) + f(X_3) + \varepsilon \qquad (1)$$

where $\hat{Y}$ is the prediction, X_1 through X_3 are the predictor variables, and ε is the deviation of $\hat{Y}$ from the observation Y. For our study, Y was the log-transformation of annual recruit abundance. A GAM is similar to a standard linear regression model except that the term f here represents a cubic spline, as opposed to a single coefficient in the case of a linear regression model. We limited the maximum number of knots in the spline to 3 to avoid severe wiggliness and thus limit any tendency towards over-fitting.

We chose the PDO index during late spring-early summer (PDO.MJJ) as our primary predictor (X_1) because it was the most highly correlated to adult recruitment (Table 2). Furthermore, we found that by taking the average of PDO.MJJ over the fours years prior to return to freshwater, we could account for apparent lags between shifts in the PDO index and large changes in recruitment during the last decade (compare Figs. 1a and b). From hereon we use PDO.MJJ-4 to refer to the four-year average of PDO.MJJ.

Table 2. Correlation coefficients[1] for log OCNR coho recruits with environmental indices

	Environmental index								
Month[2]	MEI	NPGO	NPI	ONI	PDO	SSH	SST	UWI	SPR[2]
D*JF	-0.14	0.39	0.09	-0.06	-0.22	-0.24	-0.41	0.08	
JFM	-0.16	0.35	0.04	-0.08	-0.27	-0.33	-0.40	0.20	
FMA	-0.24	0.36	0.13	-0.13	-0.33	-0.43	-0.41	0.28	
MAM	-0.26	0.40	0.23	-0.22	-0.46	-0.54	-0.39	0.41	-0.47
AMJ	-0.35	0.43	0.36	-0.26	-0.56	-0.58	-0.34	0.34	
MJJ	-0.45	0.45	-0.04	-0.25	-0.60	-0.58	-0.12	0.02	
JJA	-0.40	0.45	-0.19	-0.20	-0.54	-0.51	-0.01	-0.05	
JAS	-0.35	0.46	-0.11	-0.20	-0.44	-0.41	-0.05	-0.19	
ASO	-0.36	0.48	-0.06	-0.19	-0.30	-0.37	-0.19	-0.16	
SON	-0.33	0.48	-0.13	-0.20	-0.22	-0.31	-0.27	-0.10	
OND	-0.32	0.47	-0.08	-0.20	-0.15	-0.25	-0.35	-0.07	
NDJ**	-0.29	0.40	0.01	-0.21	-0.16	-0.30	-0.43	0.05	
J**	-0.28	0.29	0.11	-0.20	-0.21	-0.36	-0.49	0.13	

[1]Significant correlations are shaded in gray. .
[2]All months are for the calendar year of ocean entry, unless denoted by an asterisk: (*) = year prior to ocean entry, (**) = year of return to freshwater.
[3]Spring transition occurs once per year, so monthly average has no meaning. The SPR value has been placed with MAM because SPR typically occurs during these months.

We tested models which paired PDO.MJJ-4 with every other ocean environment variable during the year of ocean entry. We also tested SST in January of the return year because it has been used in the past to forecast OCNR coho. Furthermore, we examined the logarithmic transformation of the number of parent spawners $N_{spawners}$ (the number of spawners lagged by three years).

We also evaluated 3-variable models by combining PDO.MJJ-4 with every other possible pair of variables. We ranked all models by their generalized cross-validation (GCV) score. GCV is similar to ordinary cross-validation (OCV), but much faster computationally.

From the possible 2-variable models, we selected the highest ranking models with the restriction that no index was selected twice (9 models in total: 8 environmental variables plus log $N_{spawners}$). From the possible 3-variable models, we selected the 9 highest ranking models with the restriction that no environmental index appeared twice within the same model (for example, SST.FMA with SST.SON) and that every index was represented at least once. Furthermore, we did not select sets of variables that we considered to be too similar (for example, SST.JJA with UWI.JAS would be too similar to SST.MJJ with UWI.JAS to be providing any new information). We also limited NPGO to no more than one model because currently the NPGO index is not calculated in time to make actual forecasts (though it may be in the future).

The 18 selected models were further evaluated based on their full OCV score (rather than the approximate GCV used above), the Akaike information criterion (AIC), and what we term the "historical forecast skill" (HFS).

In OCV, one data point is removed from the data set, the model is refit from the remaining data points, and a prediction is made of the extracted data point. This is repeated for each data point, and the OCV score is the mean of the squares of the differences between the predictions $\hat{Y}_i$ and the observations Y_i. Normalizing by the variance and subtracting from 1 gives us another way of expressing the OCV score, which we denote as OCV*:

$$\mathbf{OCV}^* = 1 - \frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{n} (\bar{Y} - Y_i)^2} \qquad (2)$$

where $\bar{Y}$ is the mean of the observations. Note that Eq. (2) is equivalent in form as the equation for calculating R^2; only the methods of determining the $\hat{Y}_i$ are different.

The HFS is similar to the OCV in that the score is evaluated using predictions for observations not included when fitting the model. However, the HFS mimics how a model would be applied "operationally". We began by fitting the model using the first half of the dataset (1970 – 1989) and then making a forecast for the year 1990. Next, we included the year 1990 in the dataset, refitted the model, and made a forecast for 1991. This procedure was repeated until a final forecast was made for 2009. The HFS is calculated the same way as is the OCV* in Eq. (2), except $\hat{Y}_i$ and Y_i are instead the one-year lead forecasts and observations, respectively, for the period when the forecasts were made (which, in this specific case, is 1990 – 2009). Note that the HFS of a perfect forecast is 1, while an HFS of 0 would arise from forecasting (correctly) the mean $\bar{Y}$, which can be poorly known, particularly for small datasets; there is no theoretically lower bound to the HFS.

RESULTS

Among the selected 2-variable models, PDO.MJJ-4 coupled with date of spring transition (SPR) scored best across all skill measures (GCV, AIC, R^2, OCV*, and HFS) (Table 3). After SPR, the PDO index performed similarly coupled with three of the other large-scale indices (MEI, NPGO, and ONI); interestingly, all were in late fall/early winter. The next two best models included late spring-early summer SSH and winter return SST, in order.

Log spawners and NPI were the weakest second variables. Furthermore, the relationship between NPI and log recruits was contrary to our hypothesis: the model assumed lower recruitment with higher values of NPI.

Table 3. Selected models

Predictor variables[1]			Performance statistics					
1[2]	2	3	GCV	AIC	R^2	OCV*	HFS	Fore-cast[3]
PDO.MJJ	UWI.JAS	NPGO.OND	0.126	31.4	0.81	0.73	0.53	NA
PDO.MJJ	SPR	log $N_{spawners}$	0.136	35.1	0.77	0.70	0.67	206
PDO.MJJ	MEI.OND	UWI.JAS	0.140	36.1	0.78	0.69	0.50	180
PDO.MJJ	SPR	NPI.JFM	0.141	36.6	0.77	0.67	0.67	179
PDO.MJJ	SPR	MEI.OND	0.142	36.7	0.77	0.69	0.63	189
PDO.MJJ	UWI.JAS	SST.AMJ	0.144	37.1	0.77	0.68	0.42	246
PDO.MJJ	SPR	ONI.OND	0.144	37.3	0.76	0.67	0.62	187
PDO.MJJ	SSH.AMJ	UWI.JAS	0.145	37.4	0.77	0.67	0.49	208
PDO.MJJ	UWI.SON	SST.J	0.145	37.7	0.76	0.66	0.58	215
Ensemble mean[4]					*0.81*	*0.74*	*0.60*	*206*
PDO.MJJ	SPR		0.149	38.9	0.74	0.67	0.64	213
PDO.MJJ	MEI.OND		0.158	41.2	0.72	0.65	0.56	170
PDO.MJJ	NPGO.OND		0.160	41.6	0.73	0.64	0.57	–
PDO.MJJ	ONI.OND		0.161	41.9	0.73	0.62	0.55	168
PDO.MJJ	UWI.JAS		0.162	42.2	0.73	0.64	0.42	206
PDO.MJJ	SSH.AMJ		0.166	43.2	0.71	0.63	0.56	199
PDO.MJJ	SST.J		0.172	44.8	0.70	0.61	0.50	169
PDO.MJJ	log $N_{spawners}$		0.180	46.3	0.70	0.59	0.49	212
PDO.MJJ	NPI.JFM		0.180	46.6	0.68	0.59	0.52	165
Ensemble mean[4]					*0.75*	*0.67*	*0.56*	*194*

[1]Predictor variables in column-order of explanatory power and models in row order by GCV. Note that better fit is indicated by lower values of GCV and AIC, and by higher values of R^2, OCV*, and HFS.
[2]Average of prior 4 years of mean of PDO.MJJ.
[3]Forecast of 2010 OCN coho adult recruits (in thousands). The NPGO index for Oct. 2009 through Jan. 2010 was not available in time to use in forecast models.
[4]Models shaded in gray were used to calculate the ensemble mean scores.

Of the 2-variable models selected, the one with summer UWI provided the worst forecast skill (HFS) over the last two decades. UWI.JAS also showed the most striking non-monotonic relationship with log recruits. The trend between recruitment and upwelling wind strength was positive (as hypothesized) only up to a UWI of about 50 $m^3 s^{-1}$ 100 m^{-1}, after which recruitment decreased with increasing UWI.

The addition of a third variable resulted in marked improvements in the standard performance metrics (GCV, AIC, R^2, and OCV*) for all indices (Table 3). The 3-variable model with the best scores (excepting HSF) included summer UWI and NPGO.OND. In fact, UWI.JAS was included in four models; however, these five models had the lowest historical forecast skill. In fact, the HFS scores of the 3-variable models that included

UWI.JAS were actually lower than many of the HFS scores of the 2-variable models. In contrast, the 3-variable models with the highest HFS scores all included SPR.

Time series of the predictions by the fitted 3-variable models using the full time period 1970 – 2009 are shown in Fig. 2, while the time series of the models' forecasts in "operational" mode are shown in Fig. 3.

DISCUSSION

While any one of the models in Table 3 could be selected to serve as the forecast model for OCNR coho recruitment, we believe the forecasts from a selection of models could be taken into consideration when reporting a recruitment forecast. This would provide a range of possible outcomes that reflects, to some degree, the uncertainty we have in our understanding of how salmon productivity is driven by ocean conditions. However, there will always be a desire within the management community and the public to be supplied a single value (for one, it is simpler to design decision making rules based on a single value).

An alternative to selecting a single model with which to make a forecast is to take the mean of the forecasts from a set of models, or an *ensemble* of model forecasts, as it is commonly called in the climate modeling literature. We evaluated the ensemble mean forecast using three performance metrics: R^2, OCV*, and HFS (Note that the R^2 here is not precisely the coefficient of determination of a regression, but is calculated similarly). We chose a subset of the previously selected models, focusing on the 3-variable models as an example. We excluded models that contained NPI, ONI and NPGO. NPI was excluded because it was the weakest explanatory variable and the modeled relationship between NPI and log recruits was contrary to our hypothesis (the model assumed lower recruitment with higher values of NPI). ONI was excluded because it provided a very similar response as that of MEI but scored slightly lower; we did not want two variables that were essentially providing the same information. Lastly, NPGO was excluded because it currently is not calculated with sufficient lead time to be used as a forecast variable. This left us with six 3-variable models, which are shaded in gray in Table 3. The additive effects (as partial regression plots) of the variables in the 6 models are shown in Figs. 4 and 5.

The ensemble means scored as high or higher with respect to R^2 and OCV* than any of the individual forecasts in the ensemble (see Table 3). The HFS scores for the ensemble means were not as high as the highest-scoring individual models, but were still higher than most (Table 3).

Compared to the past methods of forecasting OCNR coho recruit abundance, the ensemble mean forecast of the six proposed 3-variable GAMs does very well. As shown in Fig. 6, had the method proposed here been used to make the forecasts for the period from 1996 to the present, the historical forecast skill score would have been 0.72 as compared to -0.17 using past methods.

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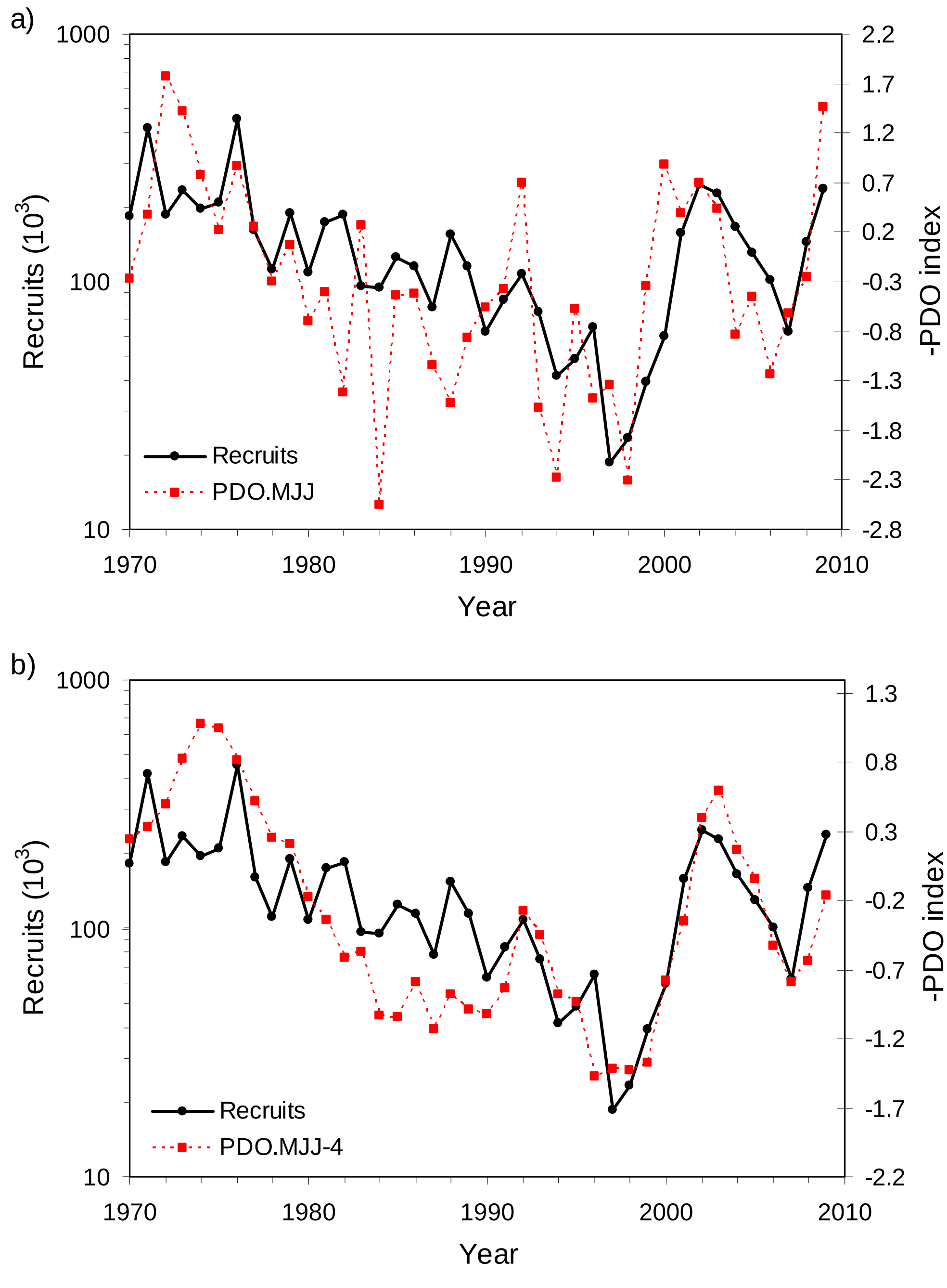

Figure 1. Time series of OCN river coho recruits during year of return to freshwater with the mean May-June-July PDO index of the ocean entry year (PDO.MJJ) (a), and with the mean of the 4 years of PDO.MJJ up to, and including, the ocean entry year (b). Note the sign of the PDO index has been reversed so that changes in recruits are in the same direction as changes in the PDO index.

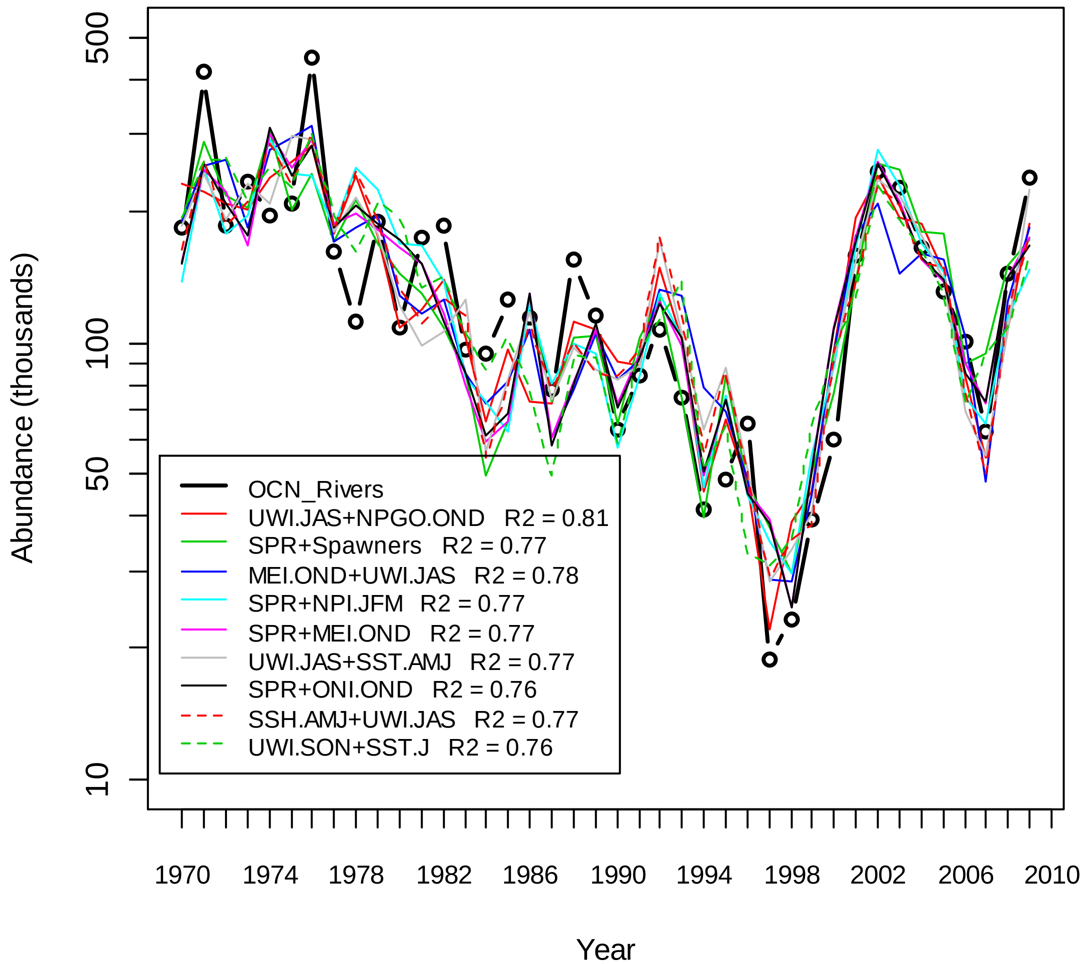

Figure 2. Time series of observed and modeled Oregon coastal natural river coho salmon adult recruits. The open circles with the thick line are the observations and the colored lines represent the predicted values from selected models using PDO.MJJ-4 combined with two additional predictor variables (as given in the legend).

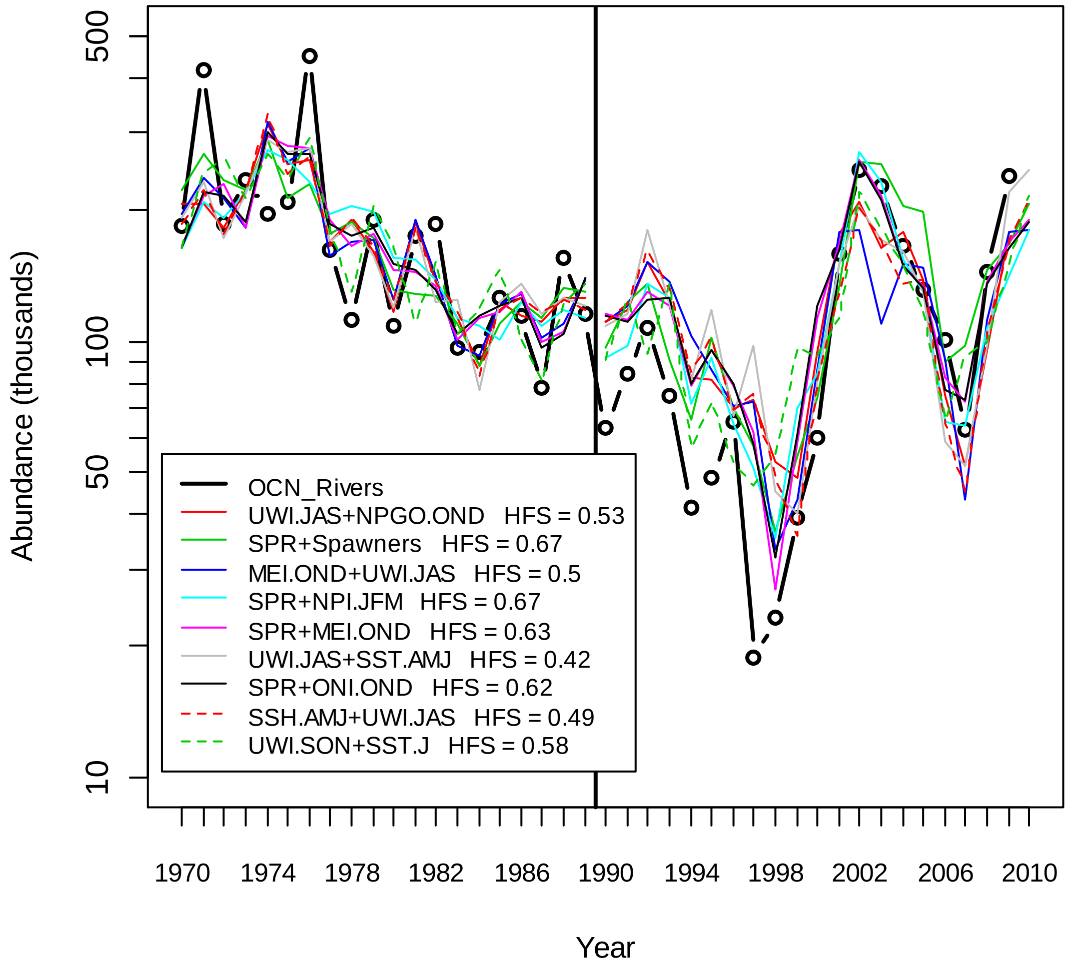

Figure 3. Time series of observed Oregon coastal natural river coho salmon adult recruits with forecasts from selected 3-variable models. The open circles with the thick line are the observations, the dashed/solid colored lines represent predictions/forecasts. The predictions shown prior to 1990 are from the models fitted to the 1970 – 1989 period, while the values for 1990 and after are 1-year lead forecasts from the models fitted to the data for all years prior to the forecast year (i.e., the models are refitted with the additional year of data prior to each forecast). Also shown is the "historical forecast skill" (HFS) for the period 1990 – 2009 (see text for details).

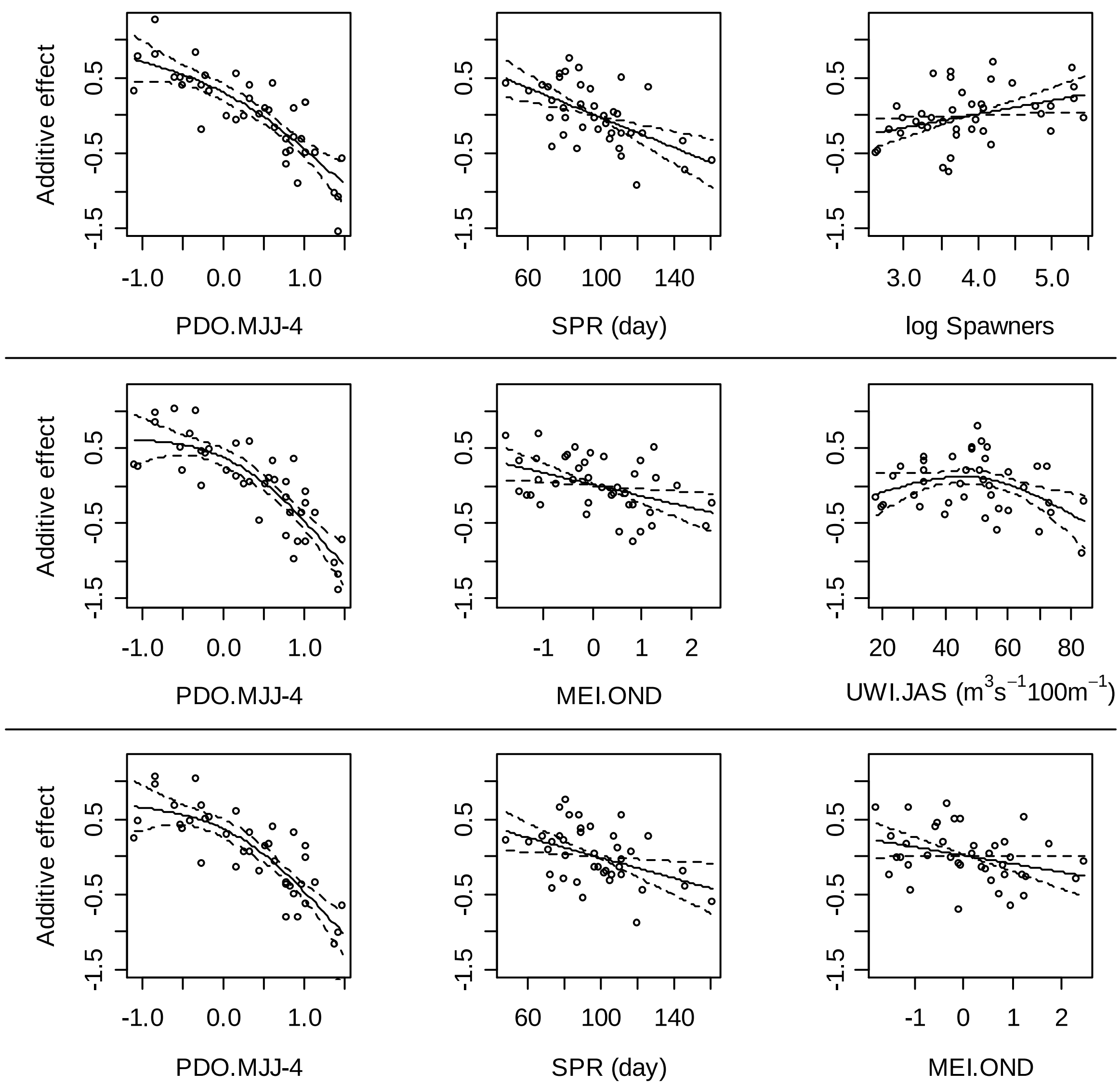

Figure 4. Partial regression plots for three of the selected three-variable GAMs listed in Table 4. Partial regression plots give the additive effect, or contribution, of each variable to the predicted log recruitment. Model variables are grouped by row and given in column order by explanatory power. Confidence limits (95%; dashed lines) and partial residuals (open circles) around the fitted lines are shown.

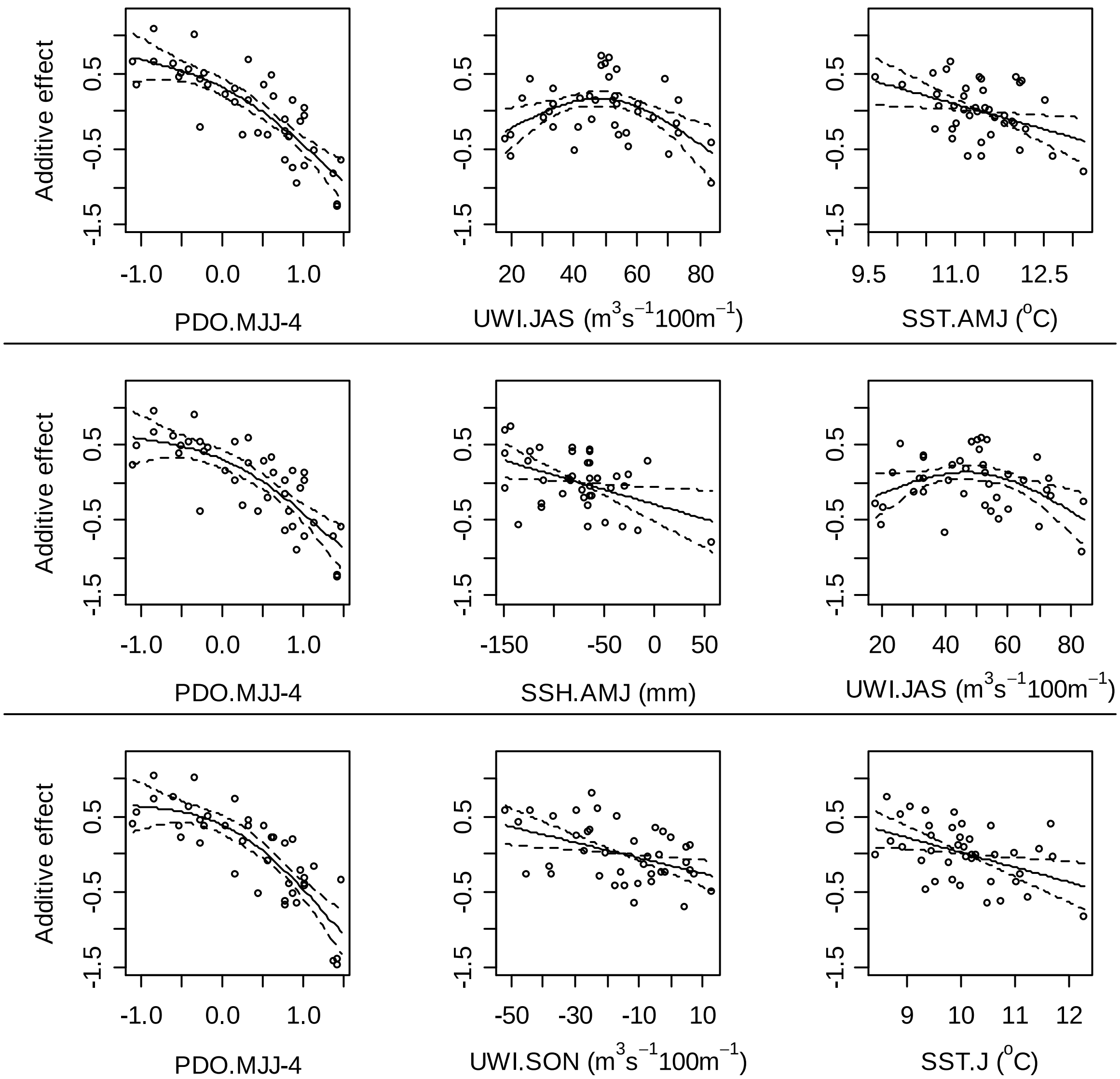

Figure 5. Partial regression plots for three of the selected three-variable GAMs listed in Table 4. Partial regression plots give the additive effect, or contribution, of each variable to the predicted log recruitment. Model variables are grouped by row and given in column order by explanatory power. Confidence limits (95%; dashed lines) and partial residuals (open circles) around the fitted lines are shown.

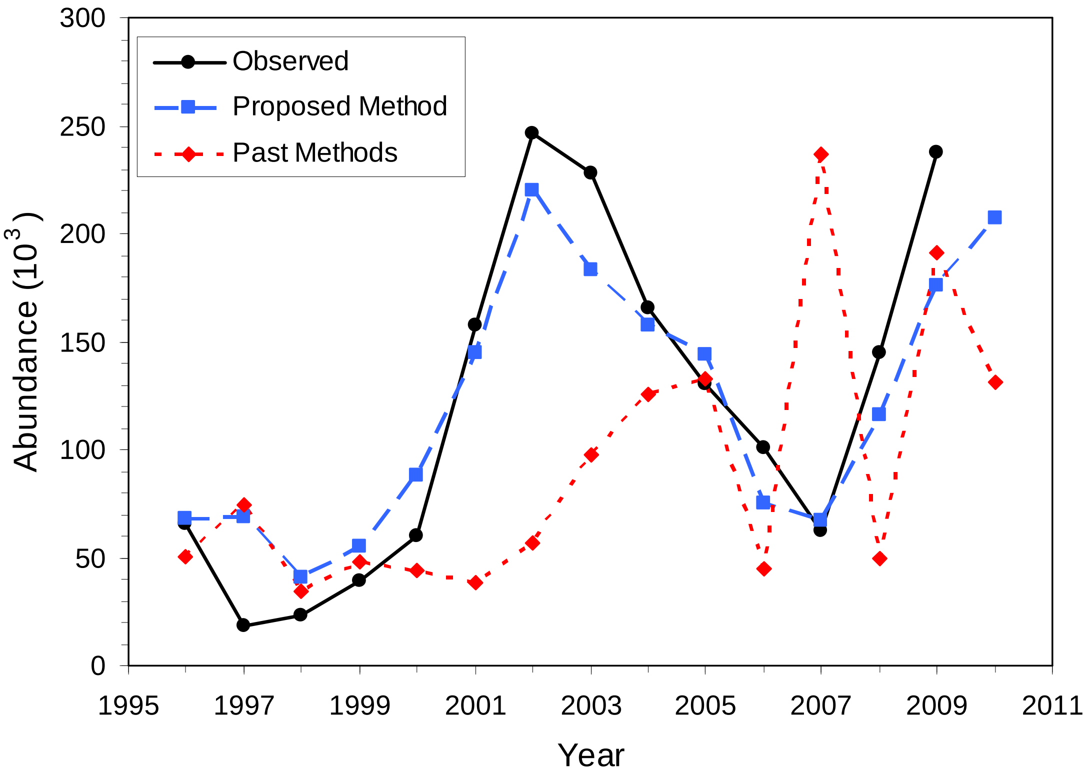

Figure 6. Observed and forecasted Oregon coastal natural river coho salmon adult recruits for the period 1996 – 2010. The blue dashed line shows the forecasts that would have been made using the method proposed in this report and the red dotted line show the actual forecasts that were made using past methods.

Forecast Models for Oregon Coast Natural Coho Salmon (*Oncorhynchus kisutch*) Adult Recruitment

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Abstract

Generalized additive models (GAMs) were used to investigate the relationships between annual recruitment of Oregon coast natural (OCN) coho salmon and indices of physical ocean environment conditions. Nine indices were examined, ranging from indices of large-scale ocean patterns (e.g., Pacific Decadal Oscillation (PDO)) to local ecosystem variables (e.g., sea surface temperature at Charleston, OR). GAMs with 2 and 3 predictor variables were evaluated using a set of performance metrics aimed at quantifying the models' skill at making short-lead (~1 year) forecasts. It was found that high explanatory power and promising forecast skill could be achieved when the spring/summer PDO averaged over the 4-years prior to the return year was used to explain the low-frequency (multi-year) pattern in recruitment while a second (or second and third) variable was used to account for year-to-year deviations from the low-frequency pattern. When averaging the predictions from a set of models (the ensemble mean) a higher skill (in terms of variance explained or cross-validation) was achieved than by selecting any single model. Making multiple forecasts from a set of models also provides a range of possible outcomes that reflects, to some degree, the uncertainty we have in our understanding of how salmon productivity is driven by ocean conditions.

1. Introduction

Short-lead (1-year) forecasts of abundance are used to set allowable harvest for West Coast salmon stocks (Pacific Fishery Management Council, 2003). Forecasts typically are based on stock-recruit relationships and/or regressions of older age returns against younger-age returns within cohorts (“sibling regressions”), such as against precocious males that return after only a few months at sea (i.e., jacks). These techniques work well for many stocks, but fail when stock accounting is inaccurate (or simply lacking for a given age, such as no jack accounting) or there are strong environmental effects on either maturation rates or mortality rates. To date, only one of these management forecasts provided to the Pacific Fishery Management Council, that for Oregon Coast Natural (OCN) coho salmon (*Oncorhynchus kisutch*), incorporates climate indicators. This is despite several efforts at developing climate-related predictors. For example, Koslow et al. (2002), Logerwell et al. (2003), Lawson et al. (2004), Scheuerell and Williams (2005) and Greene et al. (2005) provide physical descriptive models that can be used to forecast future returns for coho salmon, Snake River Spring chinook (*O. tshawytscha*), and Skagit River fall chinook salmon.

The model used to forecast annual recruits of OCN coho from rivers (coho originating in Oregon coastal lakes are treated separately) has undergone several modifications since forecasts of OCN coho recruits were first made in 1988 by the Oregon Production Index Technical Team (OPITT).

Initially (1988-1993), the forecast model was the standard Ricker spawner-recruit function (Ricker, 1954) with an ocean survival index included as an additional predictor variable (Table 1). This ocean survival index was calculated as the ratio of returns of hatchery jacks to hatchery smolts of the Oregon Production Index (OPI). There were three issues raised with this modified Ricker model:

1) The number of parent spawners within the standard density-dependent Ricker model explained little of the year-to-year variability in the number of recruits.

2) Predictions in the years this model was used were all biased high.

3) The OPI hatchery-based marine survival index was not believed to adequately incorporate environmental variability for OCN coho.

The latter concern can be seen to arise from two sources. One is that OPI (OPIH) hatchery coho survival and wild coho survival may not always align given their different life histories, ancestry, and geography (unlike OCN coho, OPI hatchery coho come predominately from the Columbia River system). A second is the fact that ocean survival accounts for only part of total survival; total coho salmon survival is believed to be roughly equally divided between the freshwater and marine life phases (Holtby and Scrivener, 1989; Bradford, 1995).

These concerns led to a review of environmental variables that could be used as predictors of OCN coho recruitment. Spring upwelling in the year of ocean entry had already been linked to coho recruitment (Nickelson, 1986; Pearcy, 1992; Lawson, 1993) while sea surface temperature of the following winter was found to be equally correlated to OCN coho recruits (Lawson, 1997). Together, spring upwelling winds and winter sea surface temperature (SST) could explain 73% of the variability in recruitment (Lawson, 1997). The selected model was a linear regression of log-transformed recruits against the spring Bakun upwelling wind index (UWI) and winter sea surface temperatures (SST) and against year (Table 1). The use of year as a predictor reflected the overall steady and approximately linear (on log-scale) decline of recruit abundance during the preceding 2.5 decades (Fig 1).

Year was removed as a predictor during the years 1996 – 1998 but reinstated in 1999. However, the dramatic increase in recruitment in 2001 and 2002 (Fig. 1) meant that year could no longer be used as a reliable predictor; hence year was again dropped from the model in 2003. Lacking this variable which (at least to up about the year 2000) helped explain a strong low-frequency pattern in annual recruitment, the model could only explain about 32% of the variability in abundance (compared to 78% with year as a variable using data from 1970 to 2000). Whereas one decade prior when UWI and SST could account for a large amount (R^2 =73%) of the variability in annual recruitment, these two environmental indices were no longer strong predictors.

In 2008, the model forecasted abundances higher than what OPITT believed were reasonable. After examining alternative models, all of which tended to forecast unusually high abundances, the official forecast was made that the 2008 abundance would be equal to the 2007 abundance.

In 2009, a variable called the “regime index” (RI) was introduced to account for the period 1990 – 2000 when recruitment was at its lowest (Table 1). The RI was set equal to 1 for the years 1990 – 2000, and to 0 for all other years. The RI along with UWI and SST explained 71% of the variability in recruitment from 1970 to 2009.

Though the RI proved to be a powerful explanatory variable, it can only be applied in retrospect once a regime has been identified (or, more appropriately, “designated”). This poses a problem for forecasting, unless we have a means of knowing (or predicting) if a regime transition is occurring.

This need for a variable that explains low-frequency patterns in the OCN recruitment time series is the motivation for this study. Though changes in freshwater habitat (e.g., terrestrial climate change, and habitat degradation and restoration) will certainly affect productivity, our focus is on the marine environment and indices of ocean conditions that are likely to influence coho production. It has been shown that ocean environment indices could explain 83% of the variability on OCN coho recruitment between 1970 and 2000 (Koslow et al., 2002), though whether this is due to positive correlation between factors promoting both freshwater and marine survival (Lawson et al., 2004) and/or to model over-fitting is debatable. In the latter case, the reliability of the model as a forecast tool needs to be considered beyond simply reporting the R^2 of the fit (Koslow et al., 2002).

We examined a suite of potential predictor variables that includes indices of both large-scale ocean conditions (Multi-variate ENSO index, North Pacific Gyre Oscillation index, North Pacific index, Ocean Niño index, and Pacific Decadal Oscillation index) and local ocean conditions (upwelling wind strength, upwelling spring transition, sea surface temperature and sea surface height). We first examined each index individually to see how well it correlated with OCN recruitment. Secondly, we built generalized additive models (GAMs) using various combinations of indices and evaluated the models in terms of their ability to make accurate forecasts. We chose GAMs because they have the powerful attribute of not imposing *a priori* a given functional relationship between the predictor(s) and the predictand. GAMs have been used previously to explore relationships between environmental variables and marine survival of OPI hatchery coho (Logerwell et al., 2003) and freshwater survival of OCN coho (Lawson et al., 2004).

2. Data and Methods

2.1. Data

2.1.1. Oregon Coast Natural (OCN) Coho salmon

The Oregon Coast Natural (OCN) coho salmon stock is naturally produced in rivers and lakes along the Oregon coast south of the Columbia River. This stock aggregate is a component of the greater Oregon Production Index (OPI) area coho stock, which also includes hatchery and natural coho from the Columbia River and hatchery coho from the Oregon coast (though coast hatchery coho have historically been a minor component of the OPI and are currently inconsequential).

Annual time series of aggregate OCN coho adult recruitment for the period 1970 – 2009 from Oregon coast rivers (OCNR) and lakes (OCNL) were generated from spawner escapement estimates (Oregon Department of Fish and Wildlife) and fishery exploitation rates (Chapter 3 in Pacific Fishery Management Council, 2010). The river and lake data were kept separate because it is believed that population dynamics differ markedly between river and lake runs (Lawson et al., 2004). This report focuses exclusively on the river (OCNR) estimates.

2.1.2. Multi-variate ENSO Index (MEI)

The Multi-variate ENSO Index (MEI) is the first principal component of six variables over the tropical Pacific: sea-level pressure (SLP), zonal and meridional components of the surface wind, sea surface temperature (SST), surface air temperature, and total cloudiness fraction of the sky (Wolter and Timlin, 1993). High values of the MEI indicate El Niño events. The unexpectedly low survival of OPI hatchery coho in the years from 1983 to 1985 has been attributed to the very strong El Niño event of 1982-83 (Pearcy, 1992). Others have pointed out that the extended El Niño period from 1990 to

1998 (with a brief La Niña in from mid-1995 through 1996) coincides the period of lowest-recorded OPI hatchery survival and OCN adult returns (Peterson et al., 2006).

2.1.3. North Pacific Gyre Oscillation (NPGO)

The North Pacific Gyre Oscillation (NPGO) index is defined as the second principal component of sea surface height (SSH) anomalies over the region 25º N-62º N, 180º W-110º W (Lorenzo et al., 2008). The NPGO index has recently been shown to be correlated with nutrient concentrations and salinity in both the Alaskan Gyre along Line P and in Southern California Current System (Lorenzo et al., 2008; 2009), which bound the northern and southern extremes of the OPI area. It is hypothesized, therefore, that the monthly mean NPGO index serves as an index of productivity, and therefore marine survival, in the greater California Current System, including the OPI area.

2.1.4. North Pacific Index (NPI)

The North Pacific Index (NPI) is an index of the strength of Aleutian Low and is calculated as the area-weighted SLP over the region 30ºN-65ºN, 160ºE-140ºW. A higher NPI signifies a weaker low with cooler air being advected to the western coast of the US and weaker winter downwelling. It has been suggested that winter ocean environment affects water column stratification, and thus productivity, the following spring (Polovina et al., 1995; Gargett, 1997; Logerwell et al., 2003). It is hypothesized, therefore, that high values of the NPI imply more productivity and increased survival. However, Ryding (1998) and Logerwell et al. (2003) did not find NPI to be a significant predictor of coho marine survival of either Washington State hatchery or OPI hatchery coho, respectively. Still, we have included monthly mean NPI as a potential large-scale regime index because it represents a region geographically closer to the OPI area than either the MEI or ONI.

2.1.5. Ocean Niño Index (ONI)

The Ocean Niño Index (ONI) is the monthly mean SST anomaly for the Niño 3.4 region (5ºN-5ºS, 120º-170ºW). Like the MEI, high values of the ONI indicate El Niño events. We use the same rationale for investigating ONI as we do for MEI (see Section 2.1.2 above)

2.1.6. Pacific Decadal Oscillation (PDO)

The Pacific Decadal Oscillation (PDO) index is defined as the first principal component of SST anomalies over the region 25ºN-62ºN, 180ºW-110ºW (Lorenzo et al., 2008). Variability in the PDO has been associated with variability in NE Pacific salmon catch (Mantua et al., 1997; Hare et al. 1999) and the PDO index has been shown to be correlated to marine survival of OPI hatchery coho (Peterson and Schwing, 2003) and survival of Alaska/British Columbia pink (*O. gorbuscha*) and sockeye (*O. nerka*) salmon (Mueter et al., 2005). Negative values of the PDO index (which imply cooler sea surface temperatures in the California current) have been associated with higher survival of salmon stocks south of Alaska; therefore we hypothesize that the same will be true for OCN coho.

2.1.7. Spring Transition Date (SPR)

The date of spring transition (SPR) marks the shift between the winter period dominated by downwelling to the summer period dominated by upwelling. The SPR generally varies from March to May. Because coho smolts migrate to the ocean from March to June, the timing of the spring transition determines the upwelling conditions that most smolts first encounter when entering the marine environment. It is therefore hypothesized that a late spring transition negatively affects early marine survival. Negative correlation has been observed between SPR and survival of Washington State and Columbia River hatchery coho smolts (Ryding and Skalski, 1999; Logerwell et al., 2003). We relied on the method of Logerwell et al. (2003), based on an analysis of daily upwelling winds and sea level, to define the date for the spring transition.

2.1.8. Sea Surface Height (SSH)

It has long been known that sea surface height (SSH) is highly correlated with current structure and wind stress over the Oregon continental shelf (Huyer and Smith, 1978; Strub et al., 1987). We therefore examined monthly SSH as an index of ocean conditions influencing OCN coho production. Between WA and northern CA, long-term and continuously updated records of SSH are available for Neah Bay, WA, South Beach, OR, and Crescent City, CA. The data from South Beach, OR (44º 37.5´ N, 124 º 02.6´ W) were chosen for this study because of the station's central location. However, data from Neah Bay and Crescent City were used to fill gaps in the South Beach data by means of linear regression relationships after the following steps were taken to process the data.

Monthly SSH was adjusted for the inverse barometric effect (e.g., Strub et al., 1987). The adjustment consisted of adding the atmospheric sea level pressure SLP anomaly to the unadjusted, or "raw", SSH:

$$\mathbf{SSH}_{adj} = \mathbf{SSH}_{raw} + 9.948(\mathbf{SLP} - 1013.3) \qquad (1)$$

where SSH_{adj} is the adjusted sea level height in units of mm and SLP has units of mb. Monthly SLP was obtained from 2.5 degree latitude x 2.5 degree longitude gridded surfaces of monthly SLP generated by the National Centers for Environmental Protection/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis I Project (Kalnay et al., 1996). The SLP values at the grid cells corresponding to the station locations were extracted from the gridded data sets.

Long-term temporal trends in SSH exist for many stations along the coast. For example, at South Beach, sea level has increased by an average of 2.37 mm a^{-1} between 1969 and 2009, inclusive, for a total of nearly 100 mm during that 41-year period. This sea level increase amounts to nearly 20% of the total variability in SSH during the same period (data not shown). We removed this trend in SSH by regressing SSH linearly against time and then taking the residuals of the fitted equation to be the final values of SSH. From hereon, it is assumed that SSH has been adjusted for the inverse barometric affect and for the long-term temporal trend.

2.1.9. Sea Surface Temperature (SST)

Several studies have found sea surface temperature (SST) to be negatively correlated to Pacific Northwest (PNW) coho survival (Lawson, 1997; Cole, 2000; Koslow et al., 2002; Logerwell et al., 2003). Furthermore, as stated previously, the mean SST for January of the adult return year has been used as a variable in linear models for practical short-lead (~1-year) forecasting of OCNR recruits since 1994 (Table 1; PFMC, 2010).

The SST series used began with a historical data set collected at the Oregon Institute of Marine Biology (OIMB) dock in Charleston, OR. This data was collected from 1966 until 1997, and was obtained from www.sccoos.org. More recent temperature data is available for the Charleston tide gauge (available at www.opendap.co-ops.nos.noaa.gov) from 1993 to the present. The OIMB data was calibrated against the tide gauge data based on monthly regressions for the overlapping years 1993-1997, and was used for 1966 to 1993. Unfortunately, the tide gauge series has gaps in 2002-2003. The nearest comparable data we could obtain for these years was SST data from the NOAA Stonewall Banks Buoy (Buoy 46050), and we used this data to fill missing values, again calibrated via linear monthly regressions for the overlapping period.

2.1.10. Upwelling Wind Index (UWI)

Many studies have linked the strength of coastal upwelling winds to favorable conditions for marine survival of PNW coho (Scarnecchia, 1981; Nickelson, 1986; Fisher and Pearcy, 1988; Holtby et al., 1990). The coastal upwelling is arguably the key process driving plankton production, and therefore the food source for coho, in the California current system (Peterson et al., 2006). As an index of coastal upwelling, we used monthly mean values of Bakun's coastal upwelling index (Bakun, 1973) for 45º N, 125º W.

2.1.11. Data Preparation

The data for each environmental variable were downloaded from the internet (see Table 2 for the URL of each data source). Three-month running means were calculated for each environmental variable with the exception of MEI which was left as a two-month running mean (the condition in which it was obtained). The following format was used to label each environmental variable:

VVV.MMM

where VVV is the three-character abbreviation of the environmental variable, MMM are the months over which the mean of variable is calculated.

12 annual time series were created for each variable using each but one of the 12 three-month running means within the calendar year. In addition, for each variable annual time series of December means and January means were generated (except for MEI).

2.2. Methods

2.2.1. Correlation Analysis

Pearson's correlation coefficient ρ was calculated for the logarithmic transformation of OCNR recruits against each environmental variable during the year of ocean entry at each of 12 monthly lags. Furthermore, ρ of log recruits against each variable for January of the return year was calculated. (Because forecasts of OCN coho salmon are made during February of the return year, January is the latest month for which data potentially can be used in a forecast.) A test was conducted to determine if ρ for a given environmental index was significantly different from zero (see Appendix A for details).

2.2.2. General Additive Models (GAMs)

We used generalized additive models (GAMs) to build relationships between ocean environment indices and OCNR recruitment. A GAM with, for example, 3 predictor variables, can be expressed in the following general form:

$$\hat{Y} = f(X_1) + f(X_2) + f(X_3) + \varepsilon \quad (2)$$

where $\hat{Y}$ is the prediction, X_1 through X_3 are the predictor variables, and ε is the deviation of $\hat{Y}$ from the observation Y. For our study, Y was the log-transformation of annual recruit abundance. The term f represents a smooth function, which in this case is a cubic spline. We limited the maximum number of knots in the spline to 3 to avoid severe wiggliness and thus reduce the degree of over-fitting. The GAMs were fit using the *mgcv* package in R.

We first tested all possible combinations of two-variable models. Given there are 14 lags per environmental index (except for SPR for which there is only one time series), this amounted to 6,441 models. The models were ranked by their generalized cross-validation (GCV) score. GCV is similar to ordinary cross-validation (OCV), but much faster computationally (Wood, 2006).

We noticed while testing all possible 2-variable combinations that those that included PDO, particularly for MJJ, consistently scored highest in terms of the GCV, no matter with which index PDO was paired. The highest R^2 achieved was 0.51 (when PDO.MJJ was paired with UWI.JJA). However, there was a notable lag between a large shift in the PDO index between 1998 and 1999 from positive to negative values (warm ocean temperatures to cool ocean temperatures) and the strong rebound of coho recruits in 2001 (Fig. 1a). This resulted in disappointing performance of the models for the period 1999 – 2004 (data not shown), which coincides with the dramatic increase to numbers in abundance not seen since 1976, and then the beginning of a nearly equally large decline (albeit more gradual).

The apparent lag in the time series between the recruit pattern and PDO pattern led us to speculate that coho production was linked not only to the ocean conditions of the ocean entry year, but that multi-year persistence of good (or poor) ocean conditions also drove recruit numbers up (or down). In other words, in took more than one "good" PDO year to cause a strong response in coho productivity.

Therefore, we examined how the PDO index average over multiple years was correlated to coho abundance and selected the average PDO.MJJ over the four years prior to the adult return year as a potential predictor variable (see section 3.1 for discussion and rationale). PDO.MJJ, therefore, served as our variable that described the low-frequency (multi-year) changes in ocean conditions (Fig 1b) and replaced those variables (i.e., year and RI) that had been used previously to achieve a similar result. From hereon, it is assumed that PDO.MJJ-4 refers to the mean PDO.MJJ of the 4 calendar years prior to the return to freshwater.

We tested models which paired PDO.MJJ-4 with every other environmental variable (excluding PDO for other months) including the logarithmic transformation of the number of parent spawners $N_{spawners}$ (the number of spawners lagged by three years). This amounted to 100 different models. We also tested models which combined PDO.MJJ-4 with every other possible pair of environmental variables (again excluding PDO) for a total of 4,950 models.

In order to limit the affects of multi-collinearity, we rejected any models for which any pair of variables had $\rho \geq 0.6$ (personal communication, Lorenzo Ciannelli, Oregon State University).

Again, we ranked the models by their GCV score. From the 2-variable models, we selected the highest ranking models with the restriction that no index was selected twice (9 models in total: 8 environmental variables plus log $N_{spawners}$). From the 3-variable models, we selected the 9 highest ranking models with the restriction that no environmental index appeared twice within the same model (for example, SST.FMA with SST.SON) and that every index was represented at least once. Furthermore, we did not select sets of variables that we considered to be too similar (for example, SST.JJA with UWI.JAS would be too similar to SST.MJJ with UWI.JAS to be providing any new information). We also limited NPGO to no more than one model because currently the NPGO index is not calculated in time to make actual forecasts (though it may be in the future). Lastly, we excluded, with one exception, all variables that included January of the return year because January data is typically not available in time for the forecasts made in February. The one exception was January SST, which has been used for forecasting OCNR coho abundance since 1994.

The 18 selected models were further evaluated based on their full OCV score (rather than the approximate GCV used above), the Akaike information criterion (AIC), and what we term the “historical forecast skill” (HFS).

In OCV, one data point is removed from the data set, the model is refit from the remaining data points, and a prediction is made of the extracted data point. This is repeated for each data point, and the OCV score is the mean of the squares of the differences between the predictions $\hat{Y}_i$ and the observations Y_i. Normalizing by the variance and subtracting from 1 gives us another way of expressing the OCV score, which we denote as OCV*:

$$\mathbf{OCV}^* = 1 - \frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{n} (\bar{Y} - Y_i)^2} \qquad (3)$$

Note that Eq. (4) is equivalent in form as the equation for calculating R^2; only the methods of determining the $\hat{Y}_i$ are different.

The HFS is similar to the OCV in that the score is evaluated using predictions for observations not included when fitting the model. However, the HFS mimics how a model would be applied in practice. We began by first fitting the model using the years 1970-1989 and then making a forecast for the year 1990. Next, we included the year 1990 into the fitting data and made a forecast for 1991. This procedure was repeated until a final forecast was made for 2009. The HFS is calculated as

$$\mathbf{HFS} = 1 - \frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{n} (\bar{Y} - Y_i)^2} \qquad (3)$$

where $\hat{Y}_i$ and Y_i are the one-year lead forecasts and observations, respectively, for the period 1990 – 2009. Note that Eq. (4) is identical to Eq. (3). The difference between HFS and OCV* (and, for that matter, R^2) is in how the $\hat{Y}_i$ are generated.

3. Results

3.1. Correlation Analysis

Of the nine environmental indices examined, PDO was found to be the most highly correlated to OCNR coho recruits, followed by SSH (Table 3). The highest correlations for these two indices occurred during the spring and early summer months of the ocean entry year (AMJ or MJJ) and were of negative sign. Other variables that showed significant correlation in spring were SST, UWI and SPR. Consistent with Lawson (1997), SST during the winter of the return year, was also significantly correlated with adult returns.

Interestingly, MEI was significantly correlated with recruits during late-spring and summer, but ONI showed no correlation with recruitment. NPI was also uncorrelated with recruits. The only significant correlation during autumn was with NPGO (SON).

As discussed in Section 2.2.2, we evaluated *N*-year averages of the PDO for each month of the year (by "monthly" we mean also the three month-running averages) as potential variables for explaining low-frequency (more than 1 year) patterns in recruitment. Through taking progressively longer averages up to $N = 4$ years, ρ between PDO.MJJ and log recruits increased from 0.60 ($N = 1$) to 0.79 ($N = 4$), while ρ decreased when N was increased from 4 to 5 years (Table 4). It is important to note that taking the *N*-year average of the environmental time series increased the degree of autocorrelation and thus increased the critical ρ needed for rejection of the null hypothesis. Even so, the correlations remained significant for PDO.MJJ up to at least $N = 5$.

3.2. General Additive Models (GAMs)

The GAM fitting showed a clear non-linear relationship between annual log recruits and PDO.MJJ-4 for all the models selected (Figs. B1-B18). The equivalent degrees of freedom (e.d.f.) for PDO ranged from 1.74 to 1.94. (To provide a reference, e.d.f. = 1 signifies a linear relationship while e.d.f. = 2 signifies a quadratic-type relationship). When coupled with PDO, NPGO and UWI were also non-linearly related to log recruits, while MEI, SPR, SSH and SST showed linear relationships (Table 5; Appendix B). NPI and ONI were either linearly or weakly non-linearly related to log recruits, depending on the model (Table 5).

Among the selected 2-variable models, PDO.MJJ-4 coupled with date of spring transition (SPR) scored best across all skill measures (GCV, AIC, R^2, OCV*, and HFS). After SPR, the PDO index performed similarly coupled with three of the other large-scale indices (MEI, NPGO, and ONI); interestingly, all were in late fall/early winter. The next two best models included late spring-early summer SSH and winter return SST, in order.

Log spawners and NPI were the weakest second variables. Furthermore, the relationship between NPI and log recruits was contrary to our hypothesis: the model assumed lower recruitment with higher values of NPI (Fig. B9).

Of the 2-variable models selected, the one with summer UWI provided the worst forecast skill (HFS) over the last two decades. UWI.JAS also showed the most striking non-monotonic relationship with log recruits (see Fig. B5). The trend between recruitment and upwelling wind strength was positive (as hypothesized) only up to a UWI of about 50, after which recruitment decreased with increasing UWI.

Time series of the predictions by the fitted 2-variable models using the full time period 1970 – 2009 are shown in Fig. 2. Time series of the models' forecasts in "operational" model are shown in Fig. 3.

The addition of a third variable resulted in marked improvements in the standard performance metrics (GCV, AIC, R^2, and OCV^*) for all indices. The 3-variable model with the best scores (excepting HSF) included UWI and NPGO. In fact, UWI was included in five models; however, these five models provided the lowest historical forecast skill. In fact, the HFS scores of the 3-variable models that included UWI were actually lower than many of the HFS scores of the 2-variable models. The 3-variable models with the highest HFS scores all included SPR.

Time series of the predictions by the fitted 3-variable models using the full time period 1970 – 2009 are shown in Fig. 4. Time series of the models' forecasts in "operational" model are shown in Fig. 5.

The restriction we imposed of eliminating from consideration those variables with January of the return year meant we excluded several models that would have scored higher than many of the models we have selected here. SSH.J in particular, stood out as a strong variable (data not show) and would have scored only below SPR among the 2-variable models. Among the 3-variable models, three models would have included variables that used January values (SSH, MEI, and ONI).

4. Discussion

We have given special attention to estimating the forecast skill of the models with the aim of avoiding *artificial skill*. A model may have artificial skill for one, or a combination, of three reasons: 1) model complexity, 2) the number of models considered, and 3) screening of predictors prior to model building (e.g., DelSole and Shukla, 2009). Model complexity may lead to over-fitting to the sample data, which itself contains error. As a model becomes more complex (e.g., as it has more fitting parameters), the parameter values begin to reflect more of the error in the data and less of the true underlying relationship. While this increases the quality of fit, it can decrease the confidence we have in a forecast.

Because the GAMs we applied here are based on cubic splines, they can be allowed to fit very complex patterns if given enough degrees of freedom. However, we limited the number of degrees by restricting the number of knots to a maximum of 3. The fitting procedure assumed many relationships to be linear, while some were roughly quadratic (Figs. B1-B18). The lack of wiggliness in the fitted relationships suggests that over-fitting is minor with the selected models.

With regards to the number of models considered, the more models that are tested, the more likely one will be found that appears to have high skill when in fact predictors and the predictand are purely independent. In order to avoid the probabilistic problem of considering very many models, or to simply reduce the computational burden, predictor screening is often carried out prior to model building/testing. Predictor screening is the practice of selecting, from a large pool of variables, those variables that are strongly correlated to the predictand. It has been show that predictor screening, however, results in over-estimation of forecast skill even when cross-validation method are used (DelSole and Shukla, 2009).

Though we examined the correlation between all possible predictor variables and log recruits, we only used the correlation coefficients to screen for the low-frequency variable (i.e., PDO.MJJ-4). Moreover, we took into consideration multiplicity when testing for significance in PDO among all months of the year. We then tested all possible combinations of 2-variable and 3-variable GAMs with PDO.MJJ-4 as the first variable, irrespective of the correlations of each predictor to the predictand. This made sense not only to avoid bias introduced by screening; the correlation strength of a predictor variable and log recruits is not indicative of how well it, as a second and/or third variable in a model, would explain the residuals of log recruits regressed against PDO.MJJ-4 only.

We are still faced with the issue of having tested a large number of models. However, we ranked them based on their generalized cross-validation score, which, unlike the R^2, is a measure of the error of the predictions of data points left out of the fitting process. This, in itself, should reduce the probability of artificial skill in the selected models. Furthermore, for the selected models we calculated two additional measures meant to help us estimate the forecast skill of the model (the ordinary cross-validation and historical forecast skill score). We would have like to have calculated the OCV* and HFS scores for every model tested, but this was computationally prohibitive.

We have avoided recommending any one particular model to serve as the forecast model for OCNR coho recruitment. We believe the forecasts from all the selected models (or a subset of the models) could be taken into consideration when reporting a recruitment forecast. This would provide a range of possible outcomes that reflects, to some degree, the uncertainty we have in our understanding of how salmon productivity is driven by ocean conditions. However, there will always be a desire within the management community and the public to be supplied a single value (for one, as single value is easier to plug into a decision making rule). An alternative to selecting a single model with which to make a forecast is to take the ensemble mean of the forecasts. We evaluated the ensemble mean against the observations using three performance metrics: R^2, OCV*, and HFS (Note that the R^2 here is not precisely the coefficient of determination of a regression, but is calculated similarly). We calculated ensemble means separately for the 2- and 3-variable models. We also excluded the models that contained NPI, ONI and NPGO. NPI was excluded because it was the weakest explanatory variable and the modeled relationship between NPI and log recruits was contrary to our hypothesis (the model assumed lower recruitment with higher values of NPI). ONI was excluded because it provided a very similar response as that of MEI but scored slightly lower; we did not want two variables that were essentially providing the same information. Lastly, NPGO was excluded because it currently is not calculated with sufficient lead time to be used as a forecast variable. This left us with six 2-variable models six 3-variable models. The ensemble means scored as high or higher with respect to R^2 and OCV* than any of the individual models (see Table 5). The HFS scores for the ensemble means were not as high as the highest-scoring individual models, but were still higher than most of the individual models (Table 5).

Compared to the past methods of forecasting OCNR coho recruit abundance, the ensemble mean of the six proposed 3-variable GAMs (which are summarized in Table 6) does very well. As shown in Table 7 and Fig. 6, had the method proposed here been used to make the forecasts for the period from 1996 to the present, the historical forecast skill score would have been 0.72 as compared to -0.17 using past methods. Note that simply forecasting the mean abundance each year (assuming the mean was accurately known) would result in a score of 0.

Notation

AIC	Akaike information criterion
GAM	Generalized additive model
GCV	Generalized cross-validation
HFS	Historical forecast skill
MEI	Multi-variate ENSO index
$N_{spawners}$	Number of OCNR coho parent spawners
$N_{jacks.OPIH}$	Number of OPIH jack returns
$N_{smolts.OPIH}$	Number of OPIH smolts
NPGO	North Pacific Gyre Oscillation
NPI	North Pacific index
OCN	Oregon Coast Natural
OCNL	OCN lakes component
OCNR	OCN riverine component
OCV	Ordinary cross-validation
ONI	Ocean Niño index
OPI	Oregon Production Index
OPIH	Oregon Production Index hatchery
PDO	Pacific Decadal Oscillation
R	Number of OCN coho adult recruits
R^2	Coefficient of determination
RI	Regime index (RI = 1 from 1990 to 2000, else RI = 0)
SLP	Sea level pressure
SPR	Spring transition date
SSH	Sea surface height
SST	Sea surface temperature
UWI	Upwelling wind index
α	Level of significance for an individual test
α_0	Level of significance for multiple tests
ρ	Pearson's correlation coefficient

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Appendix A: Testing for significant correlation

Both the OCN recruit time series and the time series of environmental variables show strong to moderate autocorrelation (data not shown). When testing for significant cross-correlation between pairs of variables, autocorrelation has the effect of increasing the probability of erroneously rejecting the null hypothesis at a given level of significance α under the assumption of serial independence. In other words, autocorrelation has the effect of reducing the number of degrees of freedom. To calculate the effective degrees of freedom under autocorrelation, we used the method of Pyper and Peterman (1998).

Moreover, when testing for significant correlation between recruits and a given environmental index, we are actually making 13 individual comparisons. This multiple testing is known as "multiplicity" and has the effect of increasing the probability of erroneously rejecting at least one null hypothesis (e.g. Katz and Brown, 1991). Various methods have been developed to account for multiple comparisons (Miller, 1981), but a very simple one is to make the following calculation for the significance level of an individual test α necessary to achieve an overall level α_0 for all K comparisons:

$$\alpha = 1 - (1 - \alpha_0)^{1/K} \tag{A1}$$

Eq. (A1) assumes the K comparisons are independent. However, the lags of the monthly means are moderately to strongly correlated (particularly given we have calculated 3-month running means). This means the effective number of comparisons is actually smaller than K.

There have been investigations into the question of coping with multiplicity given autocorrelation in the individual time series and dependency among the individual tests (e.g., correlation between lags) (Katz and Brown, 1991; Olden and Neff, 2001). However, we still lack an analytical adjustment to account for multiplicity under arbitrary autocorrelation and lag-correlation structures. Therefore, we took the simple approach of Mueter et al. (2005), which was to apply a significance level of $\alpha = 0.01$ in place of the more standard $\alpha = 0.05$, assuming that the effective number of tests ranged from $K = 5$ to 10 (out of 13) for strong to moderate correlation among lags. This meant that α_0 would range between approximately 0.05 and 0.1 for each environmental variable.

Table 1. Chronology of forecast models for OCN river coho recruits R	
Years used	Model[1]
1988-1993	$\log R = \log N_{spawners} + b_0 + b_1 N_{spawners} + b_2 N_{jacks.OPIH} / N_{smolts.OPIH}$
1994-1995	$\log R = b_0 + b_1 \mathbf{UWI.AMJ} + b_1 \mathbf{SST.J} + b_3 \mathbf{Year}$
1996-1998	$\log R = b_0 + b_1 \mathbf{UWI.AMJ} + b_1 \mathbf{SST.J}$
1999-2002	$\log R = b_0 + b_1 \mathbf{UWI.AMJ} + b_1 \mathbf{SST.J} + b_3 \mathbf{Year}$
2003-2007	$\log R = b_0 + b_1 \mathbf{UWI.AMJ} + b_1 \mathbf{SST.J}$
2008	$R_{2008} = R_{2007}$
2009-2010	$\log R = b_0 + b_1 \mathbf{UWI.AMJ} + b_1 \mathbf{SST.J} + b_3 \mathbf{RI}$

UWI.AMJ = mean upwelling winds index in April-June of ocean migration year @ 42º N 125º W
SST.J = mean sea surface temperature in January of return year @ Charleston, OR.
RI = regime index
[1]See Notation section and Section 2.1.11 for further description of terms.

Table 2. Sources for ocean indices	
Name	URL
MEI	http://www.esrl.noaa.gov/psd//people/klaus.wolter/MEI/table.html
NPGO	http://www.o3d.org/npgo/data/NPGO.txt
NPI	http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#npmon
ONI	ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/sstoi.indices
PDO	http://jisao.washington.edu/pdo/PDO.latest
SLP	http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.surface.html
SPR[1]	http://www.cbr.washington.edu/data/trans_data.html
SSH	http://ilikai.soest.hawaii.edu/uhslc/datai.html
SST[2]	http://opendap.co-ops.nos.noaa.gov/dods/IOOS/Water_Temperature.html
UWI	ftp://orpheus.pfeg.noaa.gov/outgoing/upwell/monthly/upindex.mon

[1]SPR at site listed above is still only current through 2008. This needs to be kept up-to-date or we need to provide another source for this information.
[2]SST was compiled from various sources. See text for details.

Table 3. Correlation coefficients[1] for log OCNR coho recruits with environmental indices									
	Environmental index								
Month[2]	MEI	NPGO	NPI	ONI	PDO	SSH	SST	UWI	SPR[2]
D*JF	-0.14	0.39	0.09	-0.06	-0.22	-0.24	-0.41	0.08	
JFM	-0.16	0.35	0.04	-0.08	-0.27	-0.33	-0.40	0.20	
FMA	-0.24	0.36	0.13	-0.13	-0.33	-0.43	-0.41	0.28	
MAM	-0.26	0.40	0.23	-0.22	-0.46	-0.54	-0.39	0.41	-0.47
AMJ	-0.35	0.43	0.36	-0.26	-0.56	-0.58	-0.34	0.34	
MJJ	-0.45	0.45	-0.04	-0.25	-0.60	-0.58	-0.12	0.02	
JJA	-0.40	0.45	-0.19	-0.20	-0.54	-0.51	-0.01	-0.05	
JAS	-0.35	0.46	-0.11	-0.20	-0.44	-0.41	-0.05	-0.19	
ASO	-0.36	0.48	-0.06	-0.19	-0.30	-0.37	-0.19	-0.16	
SON	-0.33	0.48	-0.13	-0.20	-0.22	-0.31	-0.27	-0.10	
OND	-0.32	0.47	-0.08	-0.20	-0.15	-0.25	-0.35	-0.07	
NDJ**	-0.29	0.40	0.01	-0.21	-0.16	-0.30	-0.43	0.05	
D	-0.29	0.41	0.06	-0.21	-0.11	-0.15	-0.38	0.05	
J**	-0.28	0.29	0.11	-0.20	-0.21	-0.36	-0.49	0.13	

[1]Significant correlations are shaded in gray. See text for explanation.
[2]All months are for the calendar year of ocean entry, unless denoted by an asterisk: (*) = year prior to ocean entry, (**) = year of return to freshwater.
[3]Spring transition occurs once per year, so monthly average has no meaning. The SPR value has been placed with MAM because SPR typically occurs during these months.

Table 4. Correlation coefficients[1] for log OCNR coho recruits with PDO					
	Years[3]				
Month[2]	1	2	3	4	5
D*JF	-0.22	-0.31	-0.36	-0.37	-0.36
JFM	-0.27	-0.38	-0.42	-0.42	-0.41
FMA	-0.33	-0.44	-0.48	-0.49	-0.47
MAM	-0.46	-0.55	-0.61	-0.63	-0.60
AMJ	-0.56	-0.65	-0.70	-0.73	-0.70
MJJ	-0.60	-0.70	-0.74	-0.79	-0.76
JJA	-0.54	-0.66	-0.72	-0.79	-0.77
JAS	-0.44	-0.58	-0.65	-0.74	-0.73
ASO	-0.30	-0.42	-0.52	-0.63	-0.64
SON	-0.22	-0.31	-0.40	-0.51	-0.54
OND	-0.15	-0.21	-0.28	-0.38	-0.42
NDJ**	-0.16	-0.23	-0.29	-0.36	-0.39
D	-0.11	-0.16	-0.19	-0.24	-0.28
J**	-0.21	-0.27	-0.33	-0.38	-0.40

[1]Significant correlations are shaded in gray. See text for explanation.
[2]All months are for the calendar year of ocean entry, unless denoted by an asterisk: (*) = year prior to ocean entry, (**) = year of return to freshwater.
[3]Number of years prior to return over which PDO was averaged.

Table 5. Selected models								
Predictor variables[1]			Performance statistics					
1[2]	2	3	GCV	AIC	R^2	OCV*	HFS	Forecast[3]
PDO.MJJ	UWI.JAS	NPGO.OND	0.126	31.4	0.81	0.73	0.53	NA
PDO.MJJ	SPR†	log $N_{spawners}$†	0.136	35.1	0.77	0.70	0.67	206
PDO.MJJ	MEI.OND†	UWI.JAS	0.140	36.1	0.78	0.69	0.50	180
PDO.MJJ	SPR†	NPI.JFM	0.141	36.6	0.77	0.67	0.67	179
PDO.MJJ	SPR†	MEI.OND†	0.142	36.7	0.77	0.69	0.63	189
PDO.MJJ	UWI.JAS	SST.AMJ†	0.144	37.1	0.77	0.68	0.42	246
PDO.MJJ	SPR†	ONI.OND	0.144	37.3	0.76	0.67	0.62	187
PDO.MJJ	SSH.AMJ†	UWI.JAS	0.145	37.4	0.77	0.67	0.49	208
PDO.MJJ	UWI.SON†	SST.J†	0.145	37.7	0.76	0.66	0.58	215
Ensemble mean[4]					*0.81*	*0.74*	*0.60*	*206*
PDO.MJJ	SPR†		0.149	38.9	0.74	0.67	0.64	213
PDO.MJJ	MEI.OND†		0.158	41.2	0.72	0.65	0.56	170
PDO.MJJ	NPGO.OND		0.160	41.6	0.73	0.64	0.57	–
PDO.MJJ	ONI.OND		0.161	41.9	0.73	0.62	0.55	168
PDO.MJJ	UWI.JAS		0.162	42.2	0.73	0.64	0.42	206
PDO.MJJ	SSH.AMJ†		0.166	43.2	0.71	0.63	0.56	199
PDO.MJJ	SST.J†		0.172	44.8	0.70	0.61	0.50	169
PDO.MJJ	log $N_{spawners}$		0.180	46.3	0.70	0.59	0.49	212
PDO.MJJ	NPI.JFM†		0.180	46.6	0.68	0.59	0.52	165
Ensemble mean[5]					*0.75*	*0.67*	*0.56*	*194*

[1]Predictor variables in column-order of explanatory power and models in row order by GCV. Note that better fit is indicated by lower values of GCV and AIC, and by higher values of R^2, OCV*, and HFS.
[2]Average of prior 4 years of mean of PDO.MJJ.
[3]Forecast of 2010 OCN coho adult recruits (in thousands). The NPGO index for Oct. 2009 through Jan. 2010 was not available in time to use in forecast models.
[4]Excludes models that contain NPGO, ONI and NPI.
†Linearly related to predictand.

Table 6. Final selected forecast models of OCNR coho recruitment								
Predictor variables[1]			Performance statistics					
1[2]	2	3	GCV	AIC	R^2	OCV*	HFS	Forecast[3]
PDO.MJJ	SPR	log $N_{spawners}$	0.136	35.1	0.77	0.70	0.67	206
PDO.MJJ	MEI.OND	UWI.JAS	0.140	36.1	0.78	0.69	0.50	180
PDO.MJJ	SPR	MEI.OND	0.142	36.7	0.77	0.69	0.63	189
PDO.MJJ	UWI.JAS	SST.AMJ	0.144	37.1	0.77	0.68	0.42	246
PDO.MJJ	SSH.AMJ	UWI.JAS	0.145	37.4	0.77	0.67	0.49	208
PDO.MJJ	UWI.SON	SST.J	0.145	37.7	0.76	0.66	0.58	215
Ensemble mean					*0.81*	*0.74*	*0.60*	*206*

[1]Predictor variables in column-order of explanatory power.
[2]Average of prior 4 years of mean of PDO.MJJ.
[3]Forecast of 2010 OCNR coho adult recruits (in thousands).

Table 7. Actual OCN river coho recruitment and forecasted recruitment using past and proposed method for the years 1996 – 2010

Year	Actual recruits (thousands)	Forecasted recruits (thousands)	
		Past Model[1]	Proposed Model[2]
1996	65.4	50.1	68.2
1997	18.7	74.3	68.7
1998	23.2	34.4	40.8
1999	39.2	48.1	54.9
2000	60.2	43.9	88.1
2001	157.6	38.1	145.0
2002	246.8	57.2	220.4
2003	227.8	97.8	183.2
2004	165.9	125.4	157.5
2005	130.5	133.1	143.6
2006	101.1	44.6	75.1
2007	62.8	236.9	67.0
2008	144.7	50.0	115.8
2009	237.8	191.4	175.8
2010	NA	131.4	207.2
HFS [3]		*-0.17*	*0.72*

[1]Actual forecast made using models given in Table 1.
[2] Mean forecast from proposed models in operational mode, i.e., 1-year lead forecasts are made from the GAMs fitted to the data for all years prior to the forecast year (i.e., the models are refitted with the additional year of data prior to each forecast).
[3]Historical forecast skill score for 1996 – 2009.

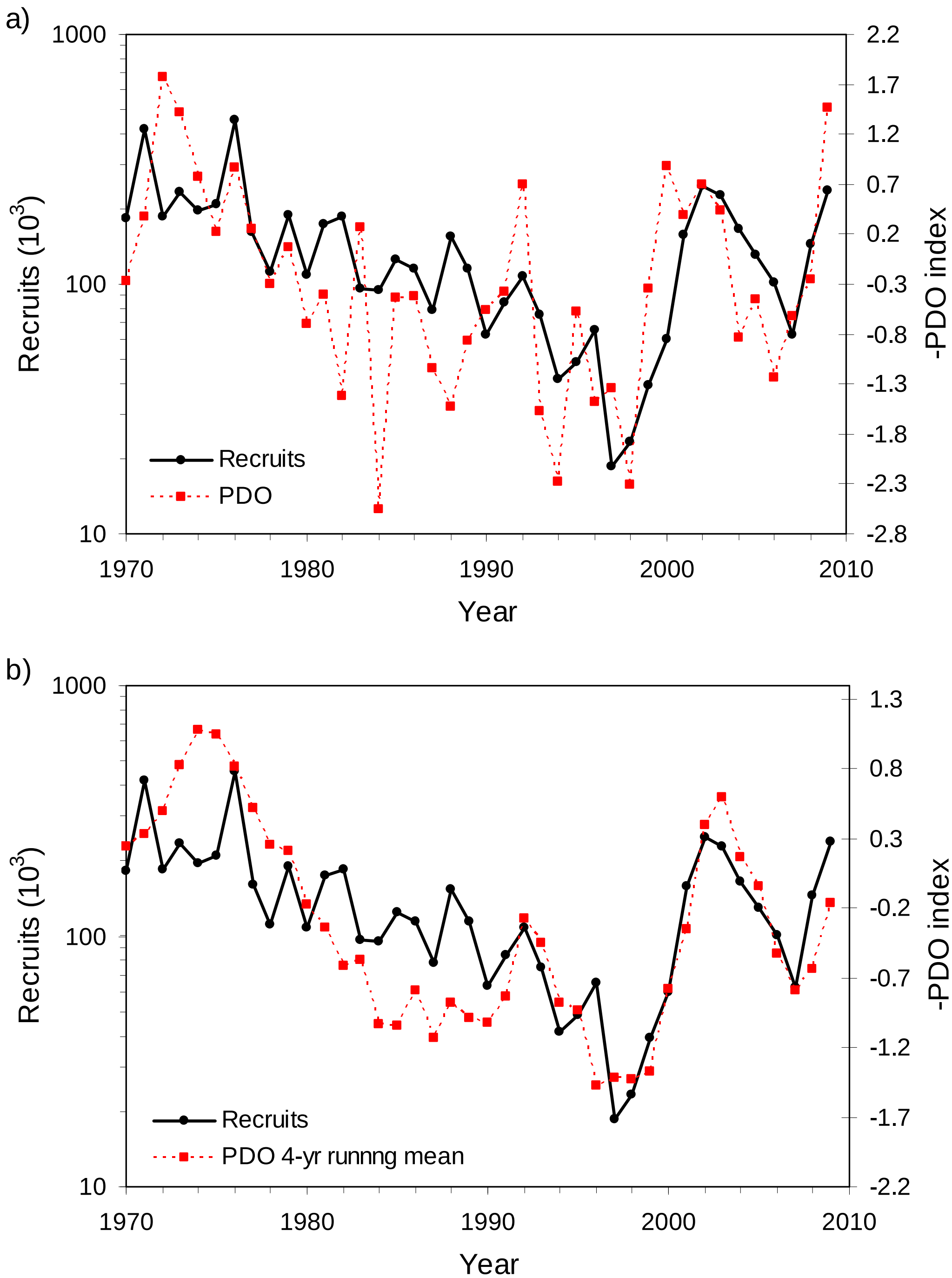

Fig. 1. Time series of OCN coho river recruits during year of return to freshwater with the mean May-June-July PDO index of the ocean entry year (PDO.MJJ.t1) (a), and with the mean of the 4 years of PDO.MJJ.t1 up to the ocean entry year (b). Note the sign of the PDO index has been reversed so that changes in recruits are in the same direction as changes in the PDO index.

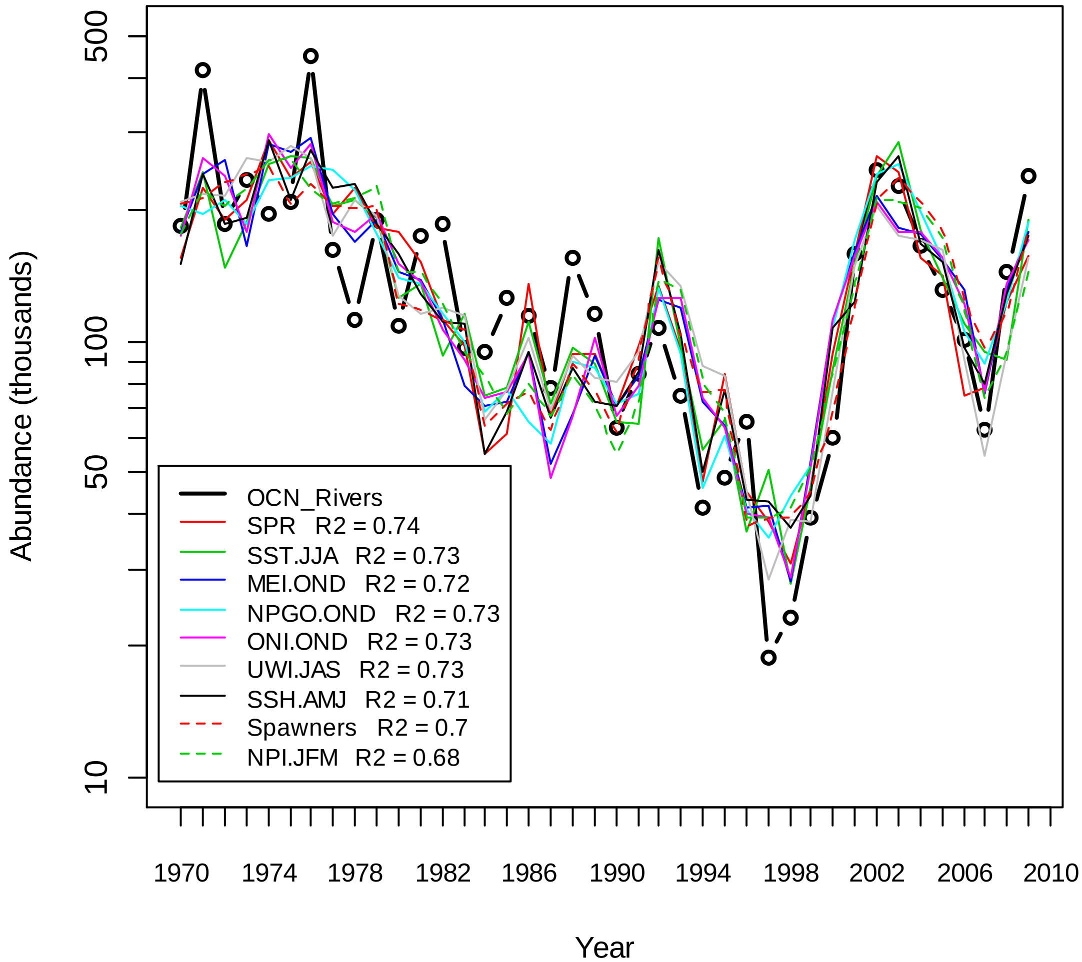

Fig. 2. Time series of observed and modeled Oregon coast natural river coho salmon adult recruits. The open circles with the thick line are the observations and the colored lines represent the predicted values from selected models using PDO.MJJ-4 combined with a second predictor variable (as given in the legend).

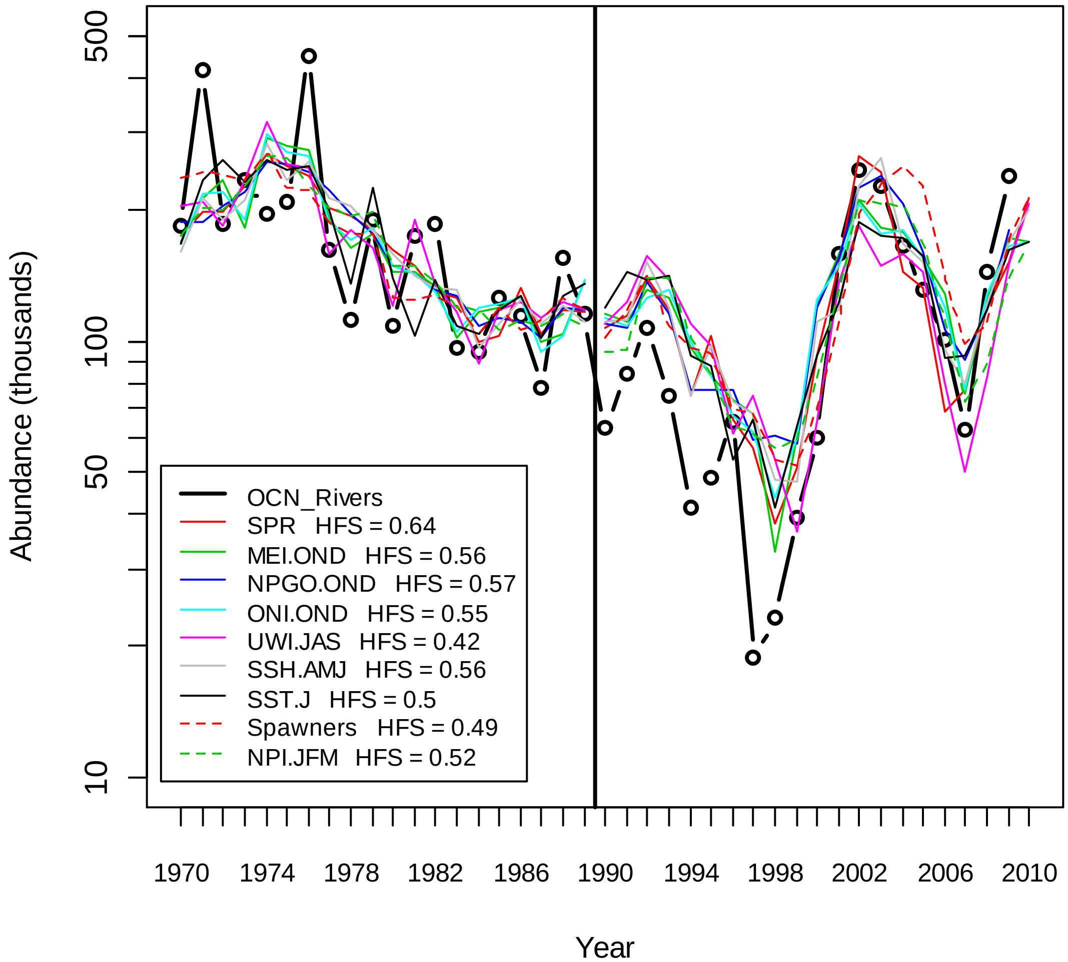

Fig. 3. Time series of observed Oregon coast natural river coho salmon adult recruits with forecasts from models using PDO.MJJ-4 combined with a second predictor variable (as given in the legend). The open circles with the thick line are the observations, the dashed/solid colored lines represent predictions/forecasts. The predictions shown prior to 1990 are from the models fitted to the 1970 – 1989 period, while the values for 1990 and after are 1-year lead forecasts from the models fitted to the data for all years prior to the forecast year (i.e., the models are refitted with the additional year of data prior to each forecast). Also shown is the "historical forecast skill" (HFS) for the period 1990 – 2009 (see text for details).

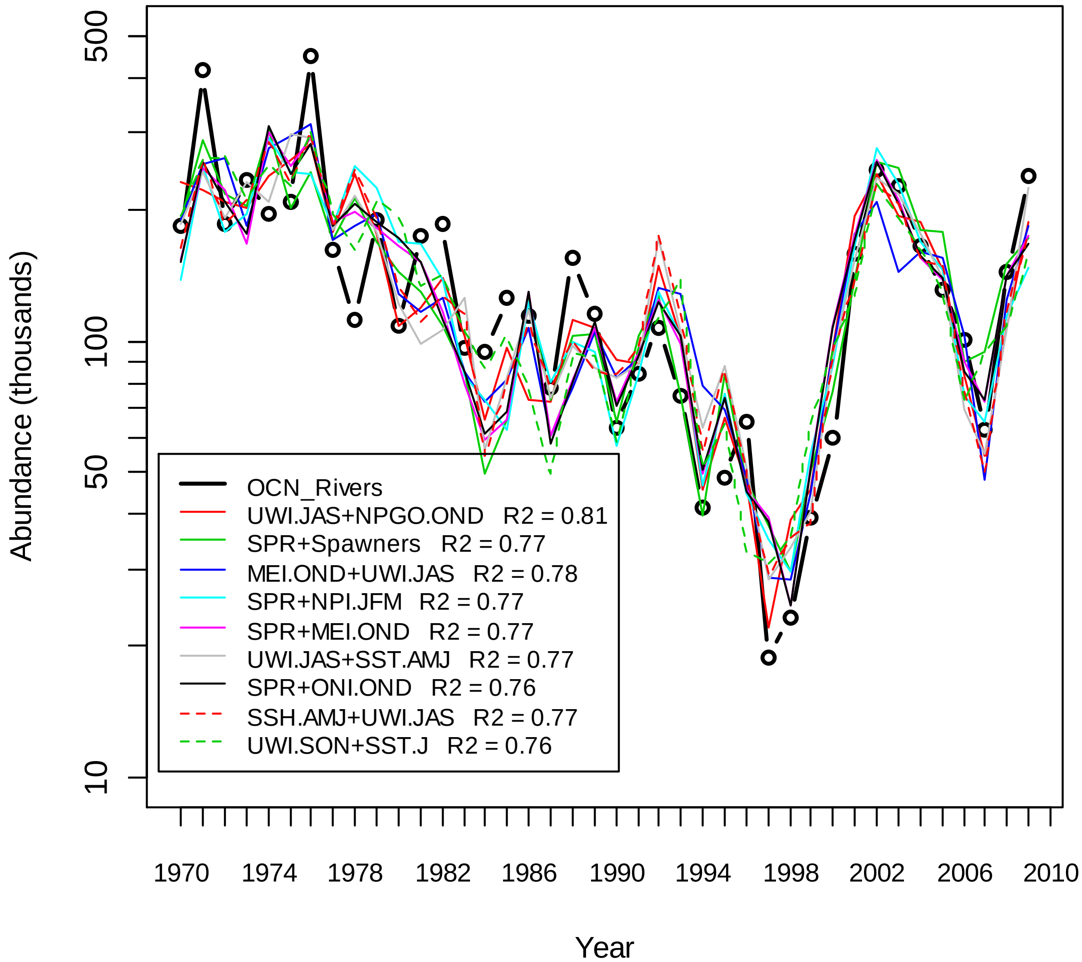

Fig. 4. Time series of observed and modeled Oregon coast natural river coho salmon adult recruits. The open circles with the thick line are the observations and the colored lines represent the predicted values from selected three-variable models.

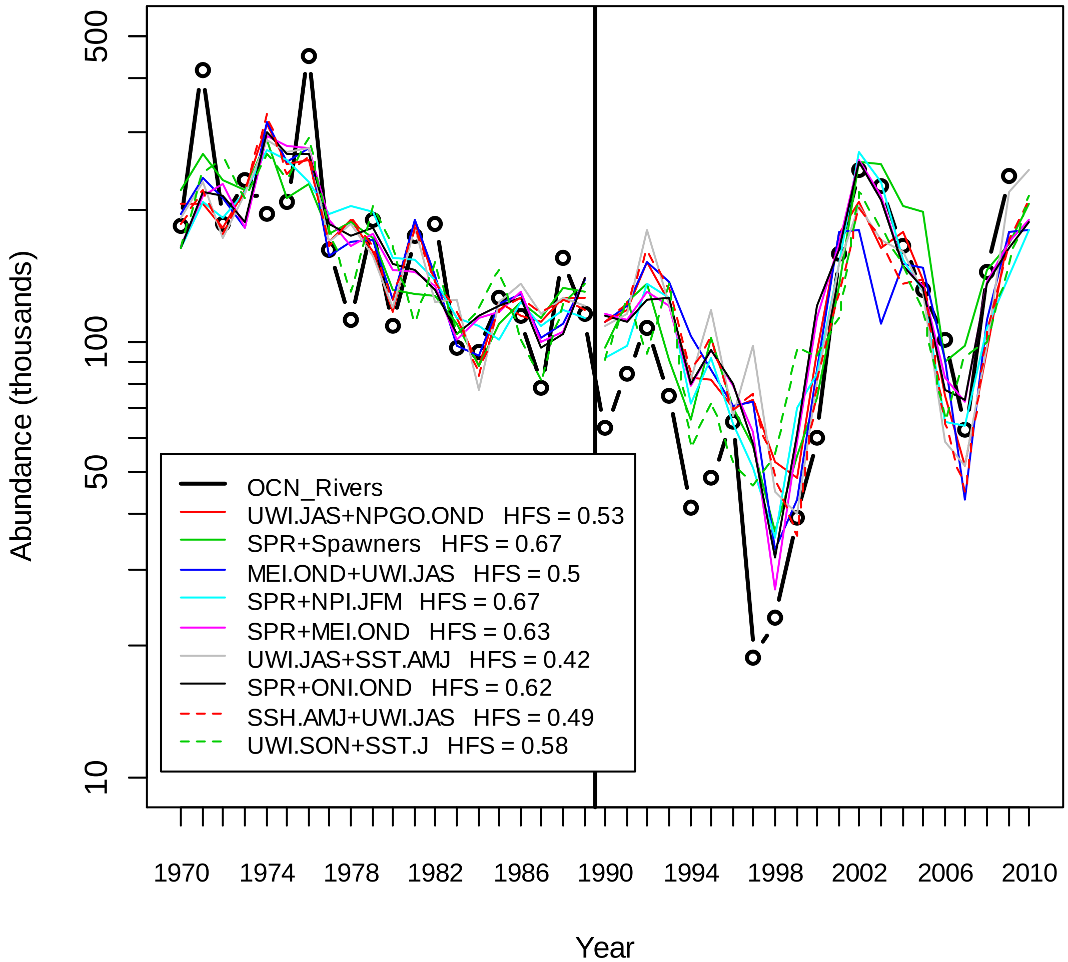

Fig. 5. Time series of observed Oregon coast natural river coho salmon adult recruits with forecasts from selected 3-variable models. The open circles with the thick line are the observations, the dashed/solid colored lines represent predictions/forecasts. See Fig. 5 caption for details.

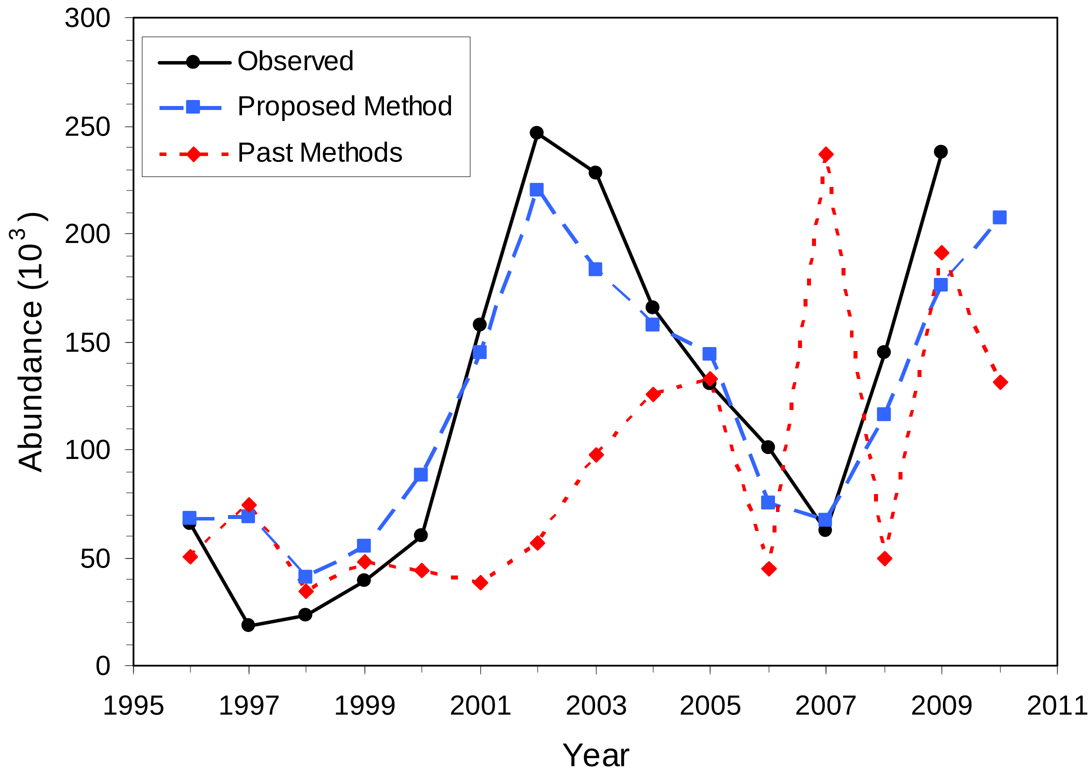

Fig. 6. Observed and forecasted Oregon coast natural river coho salmon adult recruits for the period 1996 – 2010. The blue dashed line shows the forecasts that would have been made using the method proposed in this report and the red dotted line show the actual forecasts that were made using the past methods summarized in Table 1.

Appendix B: Partial regression plots for selected GAMs

This appendix provides partial regression plots for the GAMs of Oregon coast natural river coho salmon adult recruits. Confidence limits (95%; dashed lines) and partial residuals around the fitted lines are shown.

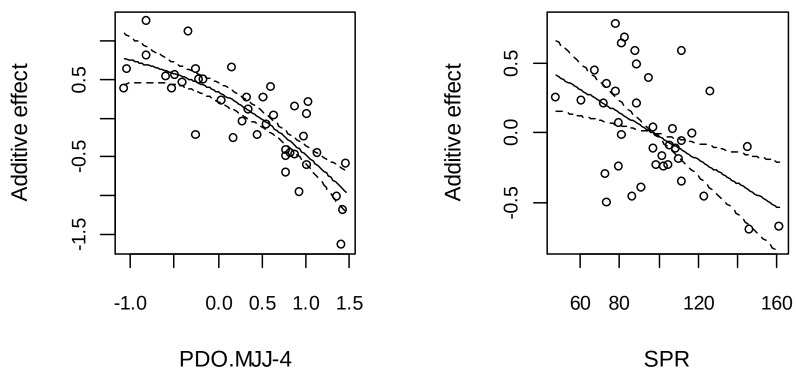

Fig. B1. Partial regression plots for log recruits against PDO.MJJ-4 and SPR.

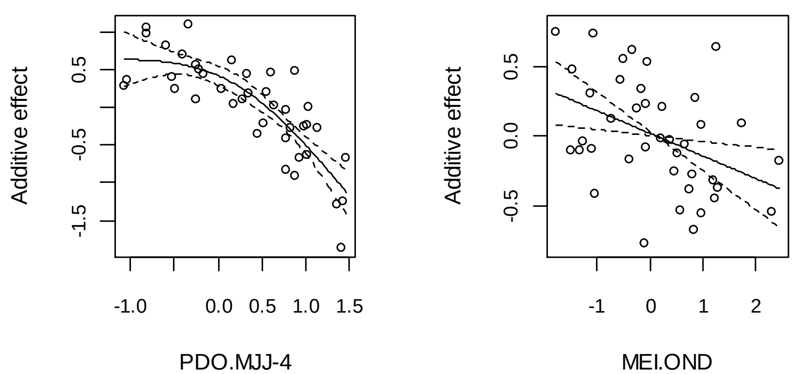

Fig. B2. Partial regression plots for log recruits against PDO.MJJ-4 and MEI.OND.

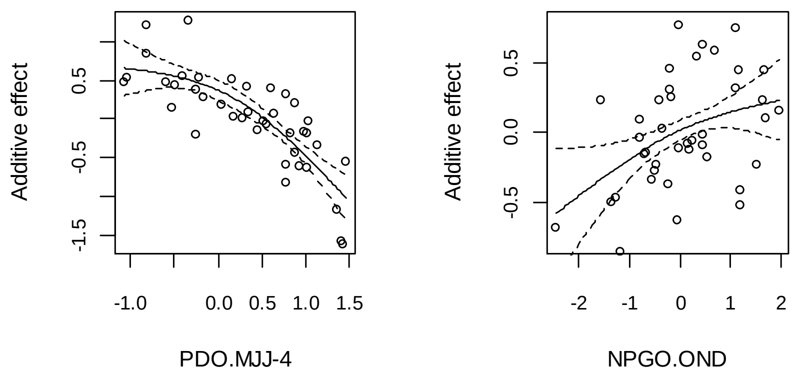

Fig. B3. Partial regression plots for log recruits against PDO.MJJ-4 and NPGO.OND.

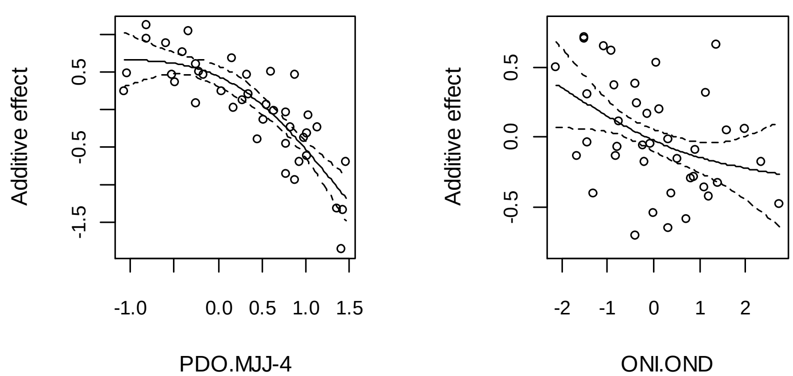

Fig. B4. Partial regression plots for log recruits against PDO.MJJ-4 and ONI.OND.

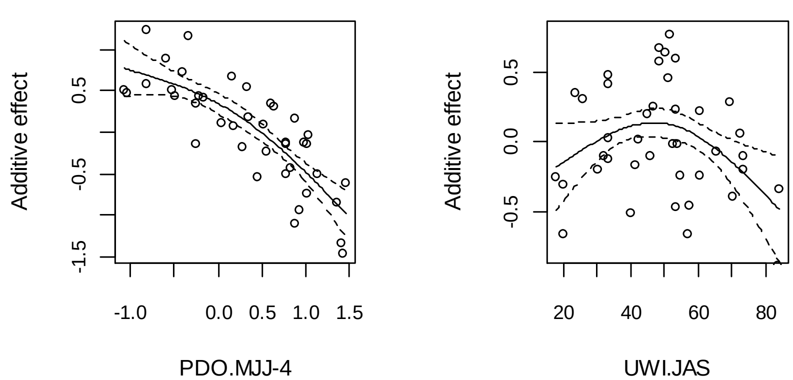

Fig. B5. Partial regression plots for log recruits against PDO.MJJ-4 and UWI.JAS.

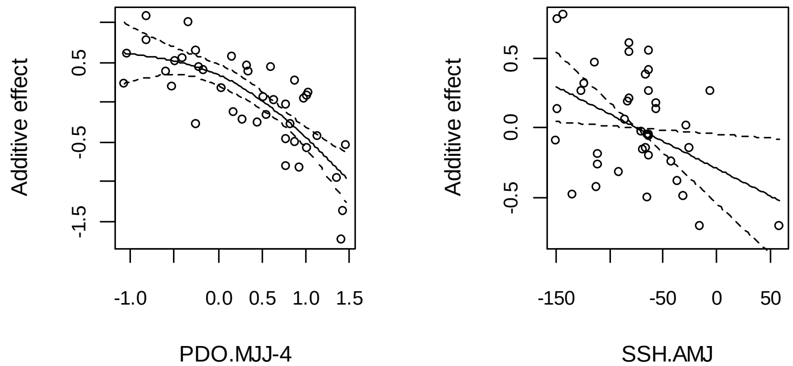

Fig. B6. Partial regression plots for log recruits against PDO.MJJ-4 and SSH.AMJ.

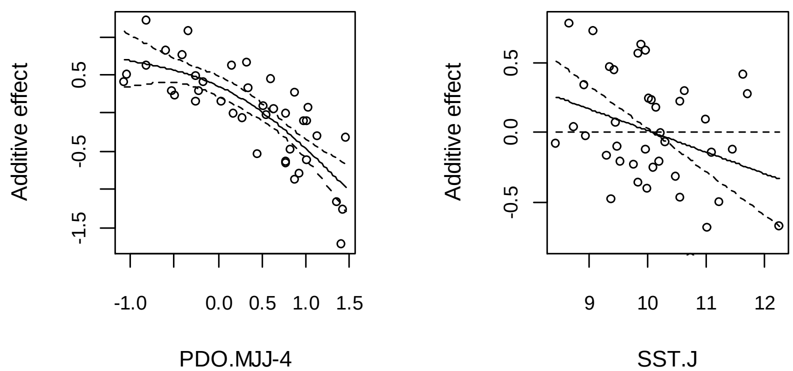

Fig. B7. Partial regression plots for log recruits against PDO.MJJ-4 and SST.J.

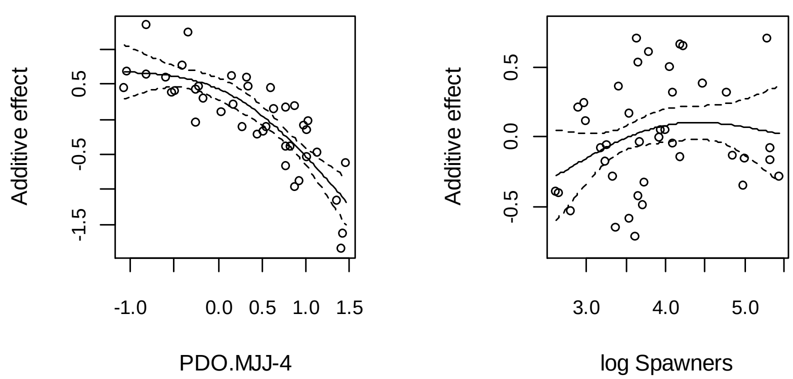

Fig. B8. Partial regression plots for log recruits against PDO.MJJ-4 and log Spawners.

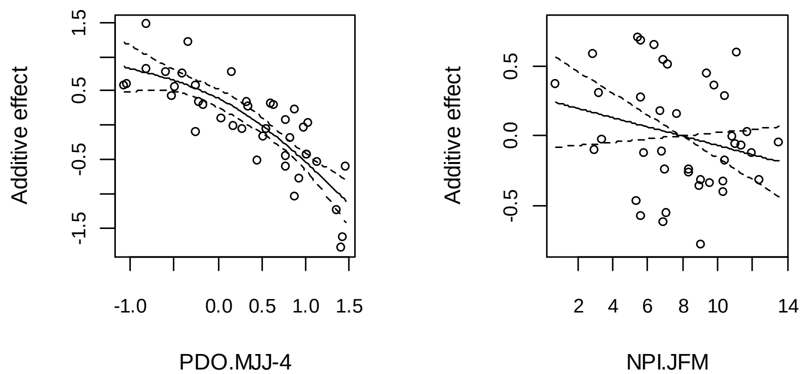

Fig. B9. Partial regression plots for log recruits against PDO.MJJ-4 and NPI.JFM.

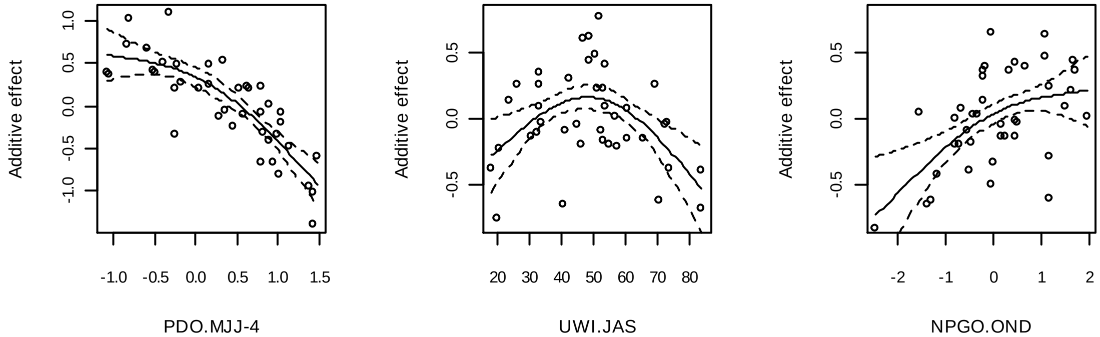

Fig. B10. Partial regression plots for log recruits against PDO.MJJ-4, UWI.JAS and NPGO.OND.

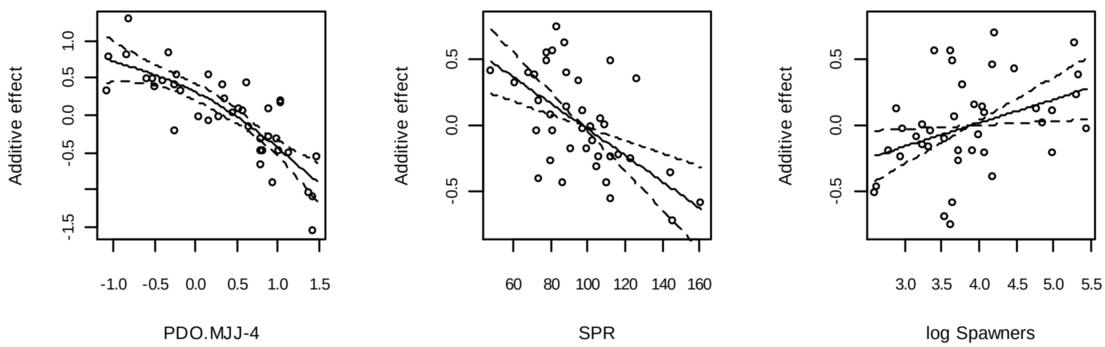

Fig. B11. Partial regression plots for log recruits against PDO.MJJ-4, SPR and log $N_{spawners}$.

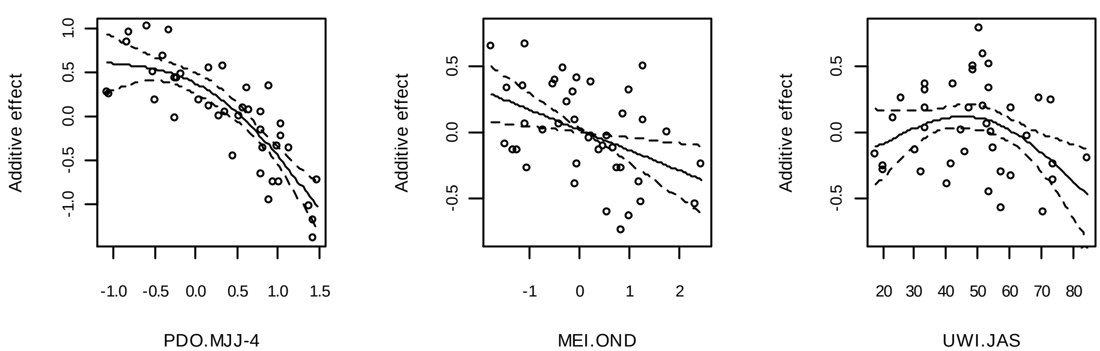

Fig. B12. Partial regression plots for log recruits against PDO.MJJ-4, MEI.OND and UWI.JAS.

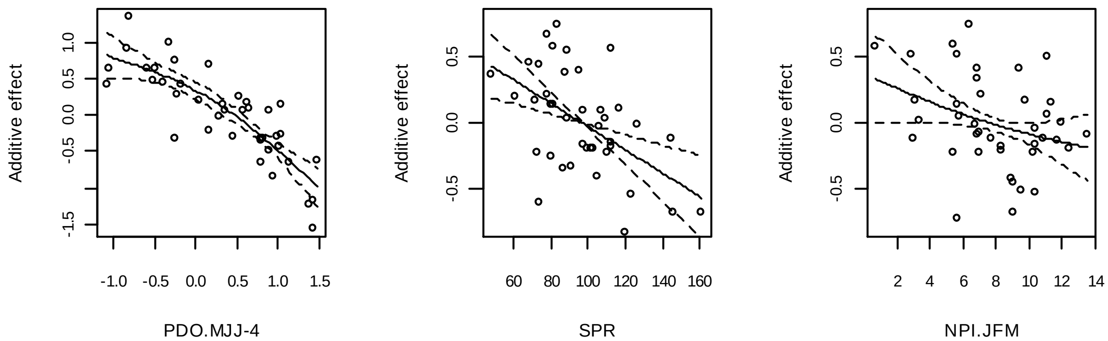

Fig. B13. Partial regression plots for log recruits against PDO.MJJ-4, SPR and NPI.OND.

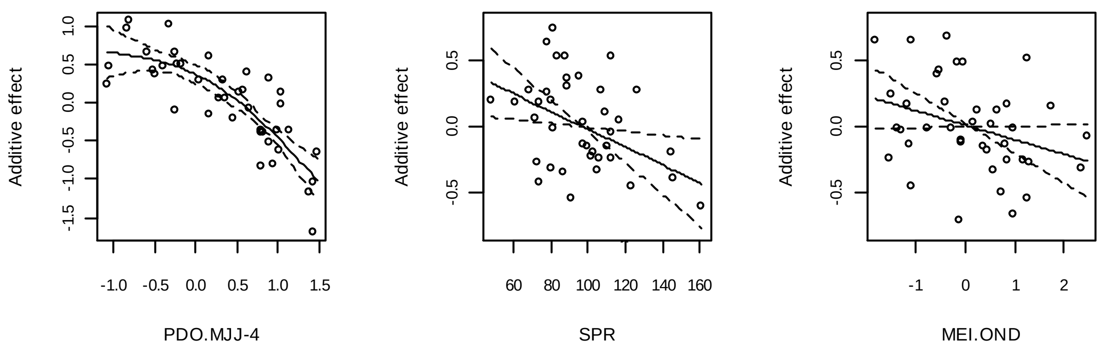

Fig. B14. Partial regression plots for log recruits against PDO.MJJ-4, SPR and MEI.OND.

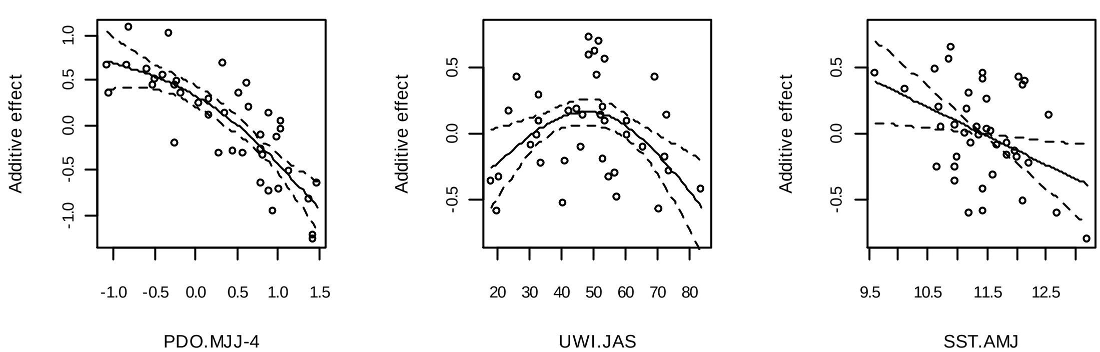

Fig. B15. Partial regression plots for log recruits against PDO.MJJ-4, UWI.JAS and SST.AMJ.

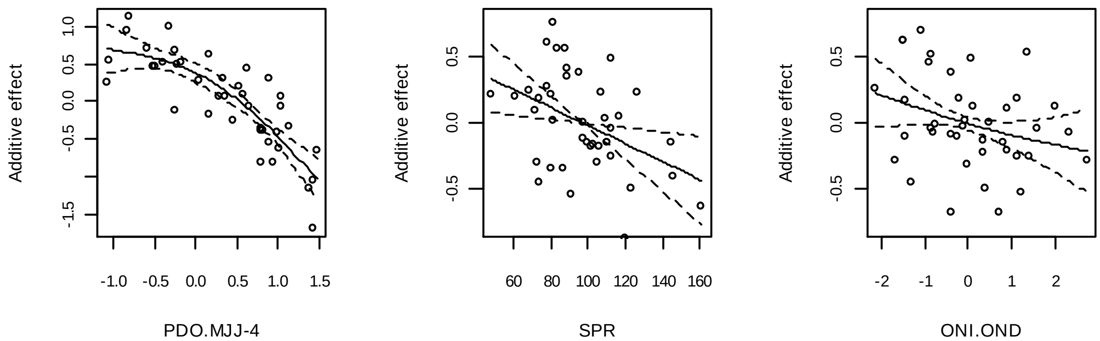

Fig. B16. Partial regression plots for log recruits against PDO.MJJ-4, SPR and ONI.OND.

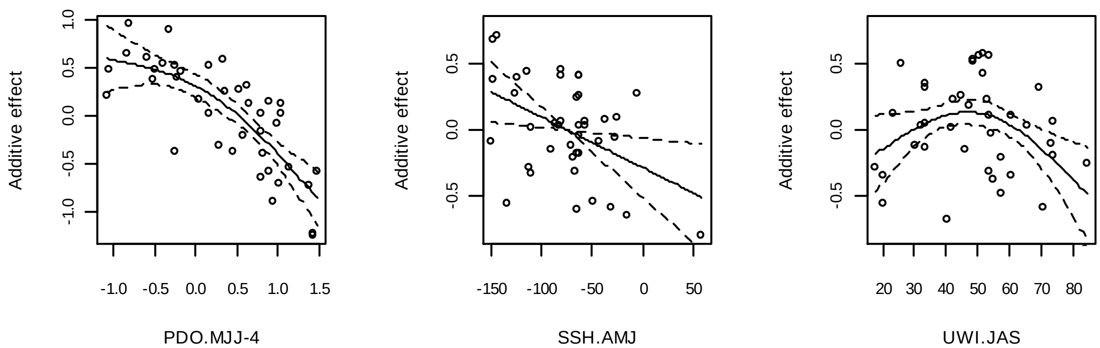

Fig. B17. Partial regression plots for log recruits against PDO.MJJ-4, SSH.AMJ and UWI.JAS.

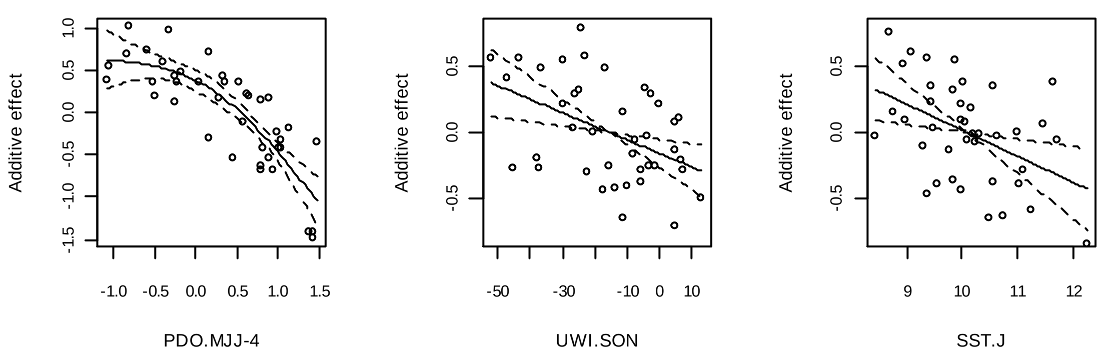

Fig. B18. Partial regression plots for log recruits against PDO.MJJ-4, UWI.SON and SST.J