Climate Vulnerability Assessment of Oregon Hatchery Programs

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Table of Contents

Report roadmap

This report is organized into three main sections. The "Summary" offers an overview of project goals, the brief review of the analytical approach, and key findings. The "Stock Synthesis" section delves into population trends and model results for all assessed hatchery stocks. The "Detailed Methodology" section elaborates on predictor variable selection, modeling, and implementation of the qualitative vulnerability assessment.

Figures and tables are divided into two sections: the “Summary" section contains all primary figures and tables referenced in the Summary text, while the "Stock Synthesis" section includes stock-specific figures and tables referenced in the Stock Synthesis text. In this section, figures and tables are grouped and numbered by species and hatchery stock with numbering consistent with the text.

Summary

Overview

The goal of this project was to assess the vulnerability to climate change impacts for a sample set of hatchery programs representing different geographic areas and primary anadromous species raised in state-managed Oregon hatcheries (Summary Figure 1). Freshwater and marine ecosystem processes can significantly influence salmon and steelhead survival, and understanding how these factors have affected historical returns can help managers evaluate the climate vulnerability of hatchery stocks. We examined stock-specific trends in smolt-to-adult returns (SARs), which represent the proportion of smolts released from the hatchery that are recovered in fisheries or as returning adult spawners. SARs are among the most consistent long-term estimators of survival for hatchery-origin stocks. Depending on the stock, adult recoveries could occur in marine fisheries, freshwater fisheries, returns to the hatchery or another collection facility, and spawning ground surveys. We collected time series data on relevant ecological indicators and used generalized additive models (GAMs) to explore both univariate and multivariate relationships with SARs for each hatchery stock.

An additional aspect of this assessment was to evaluate the climate vulnerability of resident trout stocking programs in the Department's East and West regions, incorporating insights from Oregon Department of Fish and Wildlife (ODFW) staff interviews and published data on the thermal tolerance of hatchery trout stocks. This assessment is provided in the ‘Climate vulnerability of trout stocking programs’ subsection below.

GAM predictor overview

Marine

Early marine conditions, particularly the first summer at sea, are a critical period of survival for Pacific salmon (Duffy and Beauchamp 2011). We compiled a time series dataset of 11 ecologically relevant marine indicators (Summary Table 1). For variables available on monthly or finer time scales, we developed seasonal indicators by calculating the aggregate monthly average for each variable and the mean average seasonal value for winter (January – March) and summer (June – August). To allow comparison on the same scale, all marine indicators were standardized with a mean of 0 and SD of 1 for the given time frame and location. The final time series dataset included data for the first year at sea, plus a 1-year offset (denoted as L1 for a lag of 1-year) to encompass the first two years at sea for each brood year.

Freshwater

Smolts are highly vulnerable during their downstream migration (Healey 1991), and river flow has been found to be positively correlated with survival (Notch et al., 2020). For each hatchery, we identified the nearest downriver U.S. Geological Survey (USGS) gauge station with time series data on river flow (cubic feet per second; CFS, Summary Table 2).

Hatchery

When available, we incorporated hatchery data such as average size of fish at release, the Julian day or month of release, and total number of fish released (Summary Table 2). Variables related to size or number of fish released may help assess density dependence, while variables related to timing of release may help determine optimal environmental conditions during juvenile rearing.

Methods overview

Tag filtering

We generated data sets for Chinook (*Oncorhynchus tshawytscha*) and coho salmon (*Oncorhynchus kisutch*) hatchery programs based on coded wire tag (CWT) release and recapture data from the Pacific States Marine Fisheries Commission's (PSMFC) Regional Mark Processing Center (RMIS; Summary Table 2). We generated estimates of age by subtracting the brood year from return year. We retained tag codes also used in RMIS reports ('tag status' = 1) for analysis. CWT release and recapture data was only available for one of the steelhead (*Oncorhynchus mykiss*) hatchery programs in our analysis. For other steelhead programs, we used freshwater harvest and returns to the hatchery or other collection facility to estimate SARs. To estimate adult steelhead returns by brood year, we used a fixed age structure based on the most recent and representative age-at-return information—as identified by ODFW staff with expert knowledge—for each stock.

Modeling approach

We focused our modeling efforts on hatchery stocks with relatively consistent long-term release and recovery data (Summary Table 2). We standardized all marine environmental predictors; however, freshwater and hatchery-based variables, such as river flow, fish size at release, and date of release, were not standardized to facilitate interpretation of results (keeping variables on the original scale is also useful for determining whether variables are biologically important). We utilized flexible non-linear models (generalized additive models; GAMs) to model SARs for each stock independently to consider their unique migratory timings and exposure to environmental conditions (different ocean distributions, etc.). We first fit a series of GAMs to

SAR data for each stock using a single predictor variable, in an effort to remove those that had unrealistic relationships with SARs. Based on this initial modeling, we then removed predictors with ecologically unrealistic concave-up relationships, where SAR rates were highest at extreme values. From the retained predictor variables, we generated a candidate model set that included all possible combinations of 1–3 predictors. We included river flow (cubic-feet-per-second; CFS) as a consistent predictor due to its hypothesized influence on juvenile survival. We then evaluated the support for each predictor variable across all candidate models using several metrics of predictive ability, and ranked predictors by their effect sizes, identifying those with the most significant impact on SARs. We also assessed the correlation between top predictors and noted any variables with a correlation $\geq |0.6|$ in the Stock Synthesis section. Our aim in comparing variable influence across multiple metrics and many models was to identify those predictors with the strongest relationship to SARs.

Discussion of model results

Due to natural variability across populations, the relative importance of predictors differed among stocks. In some cases, predictors that influenced survival were closely related to hatchery management practices. For example, the survival (in terms of SARs) of coho released from the Cole Rivers and Sandy hatchery programs, fall Chinook released by the Elk River and Salmon River programs, spring Chinook released by the Trask program, and steelhead released by the Alsea, Nehalem, and Wallowa programs was expected to improve with adjustments to average size, timing of release, and/or the total number of fish released. However, for many populations, marine conditions emerged as the most significant predictors of survival. Climate projections forecast rising temperatures and increased variability in marine ecosystems, from the west coast of the USA to the Bering Sea in Alaska. These changes are expected to affect marine conditions by disrupting food availability, altering migration patterns, and increasing the frequency of extreme weather events—all of which could substantially impact fish survival.

Contrary to expectations, river flow did not significantly affect survival for any of the hatchery programs analyzed; however, we anticipate that flow may become more important as climate change continues to alter water availability. River flow was not a top-ranked predictor variable, even though models frequently indicated that survival was maximized at intermediate flows. Paradoxically, in hatchery programs such as the Trask spring Chinook, Big Creek fall Chinook, Rogue (Cole Rivers) coho, Rogue (Cole Rivers) summer steelhead, and Alsea winter steelhead, we observed an inverse relationship where the highest survival occurred at both low and high flows. This unexpected pattern suggests that these results could be confounded by other factors, such as water temperature, or interactions between CFS and other variables like size at release. Additionally, these variable patterns suggest that the optimal release strategy, as it relates to flow, may change over time due to evolving environmental conditions. As a result, strategies that were once optimal may need to be re-evaluated to ensure they remain effective in the face of ongoing change.

In some hatchery programs, modeling results predicted a decrease in survival with increasing numbers of released fish. This relationship provides evidence for density dependent effects and may be driven by increased competition or disease at higher fish densities. The predicted impact of size at release and the number of fish released may also be influenced by interactions between these variables (e.g., releasing fewer but larger fish). Our modeling framework did not incorporate interactions between predictors, which could lead to imprecise results.

The scope of available data can impact the interpretation of results and future impacts. In GAMs, rug plots are used to illustrate the distribution of data points along the x-axis of a predictor variable plot, providing insight into data density. It is important to note that hatchery data like size at release often occur as a cluster around certain values (this may be true if there is little variation in size at release from a hatchery over time), which means the certainty of model predictions decreases as one moves away from these dense areas of data. This applies to environmental variables as well—the relationships derived from GAMs are based on historical data, and projecting into ranges that we have not yet observed (such as future ocean temperatures that are warmer than the historical record) can increase uncertainty.

Important predictor variables

One of the metrics we used to evaluate the predictive performance of models was Root Mean Square Error (RMSE), which indicates how far, on average, a model's predictions of SARs deviate from the actual values. The predictors with the best (lowest) RMSE values varied by candidate model; however, certain marine indices were often among the top two predictors across species and hatchery stocks: Pacific Decadal Oscillation (PDO), North Pacific Gyre Oscillation (NPGO), and Sea Surface Temperature (SST) (Summary Table 3). Together, these metrics indicate that marine conditions during the summer play a prominent role in driving fish survival.

Climate change effects on marine conditions

To understand the long-term effects of a changing climate on survival, it is helpful to forecast predictor variables into the future. Unfortunately, forecasts do not exist for the majority of the metrics that our analysis identified as important drivers. Existing studies using projected physical ocean models have summarized the direction of change for some variables. These studies suggest that while the spatial patterning of PDO may be similar under a warming climate, variability in wind stress and the amplitude of PDO is expected to decrease in the future (Zhang and Delworth 2016). Climate projections have also suggested that NPGO will increase in variability over time and become increasingly coupled with other physical processes (Di Lorenzo et al. 2008). While the intensity of upwelling in the California Current is not expected to increase in future climate scenarios, its duration is projected to slightly decrease, albeit not as much as in other upwelling-fed systems around the world (Wang et al. 2015). Finally, we expect to see increased intensity and variability around marine heat waves (MHWs), coupled with reduced mixed layer depth and increased surface warming (Oliver et al. 2019; Deser et al. 2024).

Assessing population trends

We used dynamic generalized linear models to quantify the long-term (across all years of data) and recent (across the last 5-years of data) trends in SARs, ignoring all other predictors (Summary Table 4). Many hatchery programs demonstrated a negative trend in both average long-term and short-term survival; however, some programs (e.g. Elk River fall Chinook) showed positive long-term and short-term trends. Cyclical patterns of survival were evident in many of the programs, so trend analysis results were sensitive to the particular time frame examined and the choice of a 5-year window to quantify recent trends. The short-term negative SAR trends we observed for many programs were not surprising given that the time series ended during a period of marine ecosystem disturbance (Morgan et al. 2019). Nevertheless, negative long-term SAR trends were observed for several spring Chinook and summer steelhead programs, and some of these stocks are expected to experience elevated climate vulnerability (see next sub-section).

Qualitative vulnerability assessment

To determine the biological sensitivity of Oregon hatchery salmon and steelhead stocks, we conducted a qualitative climate vulnerability assessment, adapting the framework developed by Crozier et al. (2019) to focus on factors most relevant to hatchery fish (Summary Table 5a, 5b). In this framework, an expert panel rated climate change exposure and sensitivity for salmon and steelhead stocks based on a number of attributes. Exposure and sensitivity scores were then combined into a cumulative climate vulnerability rating. Hatchery stocks identified as having the highest vulnerability were spring Chinook salmon from the Upper Willamette River, Middle Columbia River, and Snake River species management units (SMUs), as well as summer steelhead from the Middle Columbia River and Snake River SMUs. All hatchery SMUs were ranked with vulnerabilities of ‘high’ or lower, with none classified as ‘very high.’

Climate vulnerability of trout stocking programs

Oregon Department of Fish and Wildlife's resident trout stocking programs produce approximately 5 million trout annually for release into the state’s lakes and rivers. While rainbow trout (*Oncorhynchus mykiss*) make up the majority of stocked fish, other species, such as brook trout (*Salvelinus fontinalis*), brown trout (*Salmo trutta*), cutthroat trout (*Oncorhynchus clarki*), and tiger trout (a hybrid of brook and brown trout) are stocked in select water bodies. The program also includes the release of kokanee (*Oncorhynchus nerka*) in several lakes.

These stocking programs face potential vulnerabilities due to projected climate change impacts, including rising water temperatures, reduced summer stream flows, and increased wildfire risk. Higher water temperatures and diminished summer water availability can reduce hatchery rearing capacity and elevate the risk of pathogen outbreaks, which could ultimately decrease the number of fish available for stocking. Wildfires pose both immediate threats, such as direct fish losses if hatcheries are affected, and longer-term impacts on watershed water quality. These environmental changes are already influencing trout rearing at some ODFW hatcheries and are expected to accelerate, affecting not only the hatcheries but also the water bodies where trout are stocked—ultimately impacting trout growth, survival, and the overall success of the fishery.

Despite these challenges, ODFW's trout stocking programs are expected to remain resilient in the face of climate change due to several key factors. First, hatchery trout broodstocks are generally maintained at facilities with cold, stable water sources that should continue to provide optimal rearing conditions into the foreseeable future. Eggs and juvenile trout from these facilities can be relocated to other hatcheries to avoid stressful conditions and to take advantage of additional rearing capacity outside of the summer bottleneck period. For example, coastal hatcheries can stock trout in the spring, ahead of the summer's higher temperatures and lower flows. Second, stocking strategies can be adjusted to increase the likelihood that trout are caught before environmental conditions become too stressful, particularly in lakes. ODFW is already implementing in-season adaptations by adjusting stocking schedules based on water quality conditions, with plans to continue these practices in the future. Third, options for utilizing more climate-resilient trout stocks are being explored to improve survival rates and reduce losses to pathogens (Hartman and Porto 2014). For instance, ODFW is evaluating a West Virginia rainbow trout strain that has shown improved resistance to bacterial cold-water disease.

In addition to these strategies, several other adaptations are available to enhance the resilience of trout stocking programs. Infrastructure upgrades at hatcheries could bolster climate resiliency, while the use of different trout broodstocks may provide greater flexibility in fish production. Purchasing trout eggs from private hatcheries—available year-round—could allow shifts in production schedules, enabling trout to reach catchable size earlier in the year. Furthermore, adjusting the size at which fish are stocked (e.g., fingerling vs. legal size) in certain water bodies could be reconsidered based on evolving information about natural productivity and climate change impacts.

With these diverse options for maintaining production and adapting to climate change, ODFW's trout stocking programs are expected to remain resilient and viable into the foreseeable future.

END OF SUMMARY SECTION

Stock Synthesis

This section summarizes SAR trend results and relationships between SARs and predictor variables for each hatchery program. Short term SAR trends, which were based on the most recent five brood years, were negative for most Chinook and coho salmon programs and all steelhead programs (Summary Table 4). These brood years coincided with a period of widespread marine ecosystem disturbance (Morgan et al. 2019), and SARs were generally below average during this period even for programs with a positive short-term trend. Long term SAR trends, which were based on all brood years available for each program (Summary Table 2), were also mostly negative (Summary Table 4). For most programs, a cyclical pattern of survival was also evident. Therefore, long term trend analysis results were sensitive to the start and end point of the time series, including the recent downturn in SARs, and should be interpreted in that context.

The relationships between predictor variables and survival probabilities presented here are correlational and do not imply direct causation. These associations are based on observed patterns and can therefore be interpreted as potential factors influencing survival rather than as definitive causal links.

1. Spring Chinook Salmon

1. **Trask –** The average long-term trend in SARs was slightly negative (Summary Table 4, Synthesis Figure 1.1). The predictors that appear to have the greatest association with survival probability include SST, Marine Heat Wave Cover within the US Exclusive Economic Zone (EEZ), NPGO during the first summer at sea, and PDO during the second summer at sea (Synthesis Table 1.1, Synthesis Figure 1.11). The predictor with the lowest (i.e., best) RMSE score was the total number of fish released, where increasing release numbers were associated with an increased probability of survival (Synthesis Figure 1.11). Correlation between EEZ and SST during the first summer at sea was relatively high (0.77).

2. **Deschutes (Round Butte) –** SARs exhibited a decreasing trend over time, mostly due to a declining trend over the last decade (Summary Table 4, Synthesis Figure 1.2). The most influential predictors for this stock were predominantly related to summertime marine conditions encountered during the second year at sea (Synthesis Table 1.2, Synthesis Figure 1.21). The predictors with the lowest RMSE scores were SST, PDO, NPGO, SST Arc during the second summer at sea, and SST Arc during the second winter at sea. Correlation was high (≥|0.6|) between SST Arc summer L1 and PDO summer L1, SST Arc summer L1 and SST summer L1, and SST Arc summer L1 and SST Arc Winter L1. All other variables had correlations <|0.6|.

3. **McKenzie –** The average long-term trend in SARs was negative, mostly due to a decline during the first 15 years of the time series; SARs have cycled within a relatively stable range since that time (Summary Table 4, Synthesis Figure 1.3). The most influential predictors for this stock were SST, PDO, NPGO during the second summer at sea, NPGO during the first summer at sea, and NPGO during the second winter at sea (Synthesis Table 1.3, Synthesis Figure 1.31). All predictors displayed a concave down relationship with highest predicted survival occurring at intermediate values. Correlation between NPGO summer and NPGO winter L1 was 0.61, all other variables had correlations <|0.6|.

4. **Imnaha –** There was no significant average long-term trend in SARs, which generally increased over the first 20 years of the time series and then decreased more recently (Summary Table 4, Synthesis Figure 1.4). For these fish, the most important predictors of survival were summertime PDO during the first and second years at sea, as well as NPGO during the first summer at sea (Synthesis Figure 1.41). RMSE scores for these predictors were very similar (Synthesis Table 1.4). Increasing PDO during the first summer at sea was negatively correlated with survival probability. In contrast, intermediate values of summertime PDO during the second summer at sea were associated with the highest survival probability. Similarly, intermediate values of NPGO during the first summer at sea were linked to the highest survival probability. All variables had correlations <|0.6|.

5. **Rogue (Cole Rivers) –** The average long-term trend in SARs was negative, and a declining pattern was evident across shorter-term cycles within the time series (Summary Table 4, Synthesis Figure 1.5). The top predictor of survival was summertime MHW intensity, with a relatively low RMSE score (Synthesis Table 1.5). Intermediate values of MHW intensity were predicted to have the lowest survival probability. This result was

counterintuitive, as we would expect increasing MHW intensity to decrease survival. Most of the MHW data was clustered at values less than 1, meaning model accuracy likely decreased as it predicted into areas with less data (i.e., areas of greater than average MHW intensity). The bulk of the range of MHW data show a decreasing survival probability with increasing MHW intensity, whereas only ~3 data points drive the prediction of increased survival with increasing values. Correlation between the summertime EEZ cover and summertime MHW intensity was high (0.84).

2. Fall Chinook Salmon

1. **Salmon River –** The average long-term trend in SARs was slightly negative, but some of the highest SARs in the time series were observed after 2010 (Summary Table 4; Synthesis Figure 2.1). Marine predictors that appeared to drive variation in survival probability included Spring Transition Index (STI) during the second year at sea, summertime SST Arc, and NPGO (Synthesis Table 2.1, Synthesis Figure 2.11). Fish release size and number of fish released were also predicted to increase survival. Increased average size at release and intermediate release numbers were both predicted to increase survival probability. Correlation was low for all marine variables.

2. **Elk River –** The average long-term trend in SARs was slightly positive (Summary Table 4, Synthesis Figure 2.2). The primary predictors associated with survival were average weight at release, NPGO during the second winter at sea, and the Bifurcation Index during the first year at sea (Synthesis Table 2.2, Synthesis Figure 2.21). CFS was not included in this model (Summary Table 2). Increasing the average weight of fish at release was related to an increasing probability of survival. Higher NPGO values during the second winter at sea were also associated with increased survival probability until plateauing at higher values. Higher values of the Bifurcation Index during the first year at sea were associated with increased survival probability. Correlation was low for all marine variables.

3. **Big Creek –** There was no significant average long-term trend in SARs (Summary Table 4, Synthesis Figure 2.3). Key factors that appeared to affect survival included NPGO during the second winter at sea, SST during the first summer at sea, and PDO during the second summer at sea (Synthesis Table 2.3, Synthesis Figure 2.31). An increase in NPGO during the second winter was linked to higher survival probabilities, while higher SST during the first summer and higher PDO during the second summer were both associated with lower survival probabilities. EEZ during the second summer at sea and PDO during the second summer at sea were correlated (0.64), as were EEZ during the second summer at sea and SST during the second summer at sea (0.64).

3. Coho Salmon

1. **Rogue (Cole Rivers) –** The average long-term trend in SARs was negative, and a declining pattern was particularly evident during the last 15 years of the time series (Summary Table 4, Synthesis Figure 3.1). The predictors associated with survival were SST and PDO during the second winter at sea, and the average release weight of fish

(Synthesis Table 3.1, Synthesis Figure 3.11). At winter SST values greater than the standardized mean, survival was predicted to decrease, whereas increasing winter PDO values were predicted to increase survival. Releasing fish at an average release weight of up to ~42.5g was positively correlated with survival. Correlation was low for all marine variables.

2. **Big Creek –** The average long-term trend in SARs was slightly negative (Summary Table 4, Synthesis Figure 3.2). Predictors with the greatest impact on survival included summertime MHW intensity, SST Arc during the first summer at sea, and PDO during the second summer at sea (Synthesis Table 3.2, Synthesis Figure 3.21). Increasing MHW values and higher than average SST Arc values were both correlated with decreased survival probabilities. Intermediate values of PDO were linked to higher survival probability. Correlation was high between summertime MHW intensity and summertime SST Arc (0.72), and between summertime SST Arc and summertime PDO during the second year at sea (0.66).

3. **Sandy –** The average long-term trend in SARs was negative, mostly due to a decline over the first 20 years of the time series. SARs have cycled within a relatively stable range since that time (Summary Table 4, Synthesis Figure 3.3). The most important drivers of survival appeared to be PDO during the second summer at sea, total number of fish released, and NPGO during the first summer at sea (Synthesis Table 3.3, Synthesis Figure 3.31). Increasing the number of fish released increased survival probability. Correlation was low for all marine variables.

4. Summer Steelhead Trout

1. **Siletz –** The average long-term trend in SARs was slightly negative (Summary Table 4). SARs showed an increasing trend from the 1990s until the early 2000s, after which there was a noticeable decline that continued through the 2010s (Synthesis Figure 4.1). The predictors impacting survival were NPGO during the first and second summer at sea, and SST recorded at Station P during the second summer at sea (Synthesis Table 4.1, Synthesis Figure 4.11). Intermediate values of NPGO during the first summer at sea and SST at Station P during the second summer at sea were correlated with the highest probability of survival. Increasing values of NPGO during the second summer at sea were also correlated with a higher probability of survival. NPGO during the first summer at sea and NPGO during the second winter at sea were correlated (0.61).

2. **Rogue (Cole Rivers) –** The average long-term trend in SARs was negative (Summary Table 4, Synthesis Figure 4.2). Predictors with the highest impact to survival were SST during the second winter at sea, SST Arc during the first winter at sea, and STI (Synthesis Table 4.2, Synthesis Figure 4.21). The highest probability of survival was correlated with intermediate values of both STI and SST during the second winter at sea. Higher values of wintertime SST Arc were also correlated with higher survival probability. SST Arc and SST during the second winter at sea were highly correlated (0.82), summertime PDO and SST Arc during the second summer at sea were also correlated (0.66), as were SST Arc during the second winter and second summer at sea (0.66).

3. **Deschutes (Round Butte) –** SARs showed a clear declining long-term trend (Summary Table 4; Synthesis Figure 4.3). It is important to note that this program had a shorter SAR time series than other summer steelhead programs. The key factors that appear to be impacting the survival of this stock were NPGO during the second summer at sea and first winter at sea, and SST recorded at Station P during the second winter at sea (Synthesis Table 4.3, Synthesis Figure 4.31). All these relationships exhibited a concave-down pattern, with the highest probability of survival occurring at intermediate values. Correlation was low for all marine variables.

4. **Wallowa –** The average long-term trend in SARs was negative (Summary Table 4), but examination of the SAR data indicated a trend in which SARs increased for many years and then declined over the last eight years of the time series (Synthesis Figure 4.4). The top predictors of survival for this stock were the total number of fish released, NPGO during the first summer at sea, and the STI (Synthesis Table 4.4, Synthesis Figure 4.41). Increasing the number of fish released was predicted to decrease the probability of survival. Intermediate values of NPGO during the first summer at sea were associated with the highest probability of survival, while intermediate values of STI were linked with the lowest probability of survival. Correlation between summertime SST and EEZ cover was high (0.77).

5. Winter Steelhead Trout

1. **North Fork Nehalem** – There was no significant average long-term trend in SARs, which increased over the first 20 years of the time series and then decreased in recent years (Summary Table 4, Synthesis Figure 4.5). The primary predictors associated with survival were STI, NPGO during the first summer at sea, and the Bifurcation Index during the second year at sea (Synthesis Table 4.5, Synthesis Figure 4.51). STI and NPGO during the first summer at sea both exhibited a concave-down pattern with the highest probability of survival occurring at intermediate values. Increasing values of the Bifurcation Index during the second year at sea were correlated with a decreasing survival probability. Correlation was low for all marine variables.

2. **Alsea** – The average long-term trend in SARs was slightly negative (Summary Table 4). Similar to several other steelhead programs, SARs initially exhibited an upward trend and then declined more recently (Synthesis Figure 4.6). The predictors with the greatest impact on survival were the total number of fish released, STI during the second year at sea, and NPGO during the second winter at sea (Synthesis Table 4.6, Synthesis Figure 4.61). Both STI and NPGO exhibited concave-down relationships, with the highest probability of survival occurring at intermediate values. In contrast, increasing the total number of fish released was correlated with a decreased survival probability. Correlation was low for all marine variables.

END OF SYNTHESIS SECTION

Detailed Methodology

Marine predictor variables

Basin-scale predictors

Basin-scale climate indices have been linked to Pacific salmon productivity across many studies (sensu. Mantua and Hare 2002). Based on this previous work, we considered two basin scale indices, the Pacific Decadal Oscillation (PDO) and the North Pacific Gyre Oscillation (NPGO). The PDO is the dominant year-round pattern of monthly North Pacific Sea surface temperature (SST) variability calculated as the leading Empirical Orthogonal Function (EOF)/ Principal Component (PC) of North Pacific monthly SST variability (poleward of 20°N) (Mantua and Hare 2002). The PDO is a statistical pattern that integrates multiple physical processes, including heat fluxes and wind driven transport related to the Aleutian low (Newman et al. 2016), and it is commonly related to inverse production regimes of Pacific salmon (*Oncorhynchus* spp.) in the Gulf of Alaska and California Current Ecosystem. Like the PDO, the NPGO is a statistical pattern derived using EOF/PC defined as the 2nd dominant mode of sea surface height variability in the Northeast Pacific which captures variability in North Pacific gyre strength. The NPGO is associated with regional and basin-scale variations in wind-driven upwelling and horizontal advection, which control salinity and nutrient concentrations important for phytoplankton fluctuations in the California Current Ecosystem (Di Lorenzo et al. 2008).

We also considered SST Arc as a marine driver of Pacific salmon. Briefly, SST Arc is an indicator of SST variability that spatially resembles the PDO but shows a stronger relationship to SSTs near the North American coast and a weaker connection to those in the central Pacific (Johnston and Mantua 2014). Like the PDO, SST Arc is derived as the leading mode of monthly SST anomalies (derived from empirical orthogonal function; EOF) from monthly gridded NCEP SST data across 60°N–20°N and 180°W–100°W from 1900 - 2012. Notably, SST Arc is used as a physically based metric of the leading EOF mode where a 1 standard deviation anomaly of the leading mode corresponds to an SST Arc deviation of 0.46 °C (Johnston and Mantua 2014), thus, representing regional variability that is more tightly coupled with the northern California Current than other basin-scale metrics like the PDO.

Regional predictors

Sea surface temperature at ocean entry can impact juvenile salmon marine survival. Monthly, gridded SST data is available from the NOAA 0.25 degree Daily Optimum Interpolation Sea Surface Temperature (OISST) climate data record, a data interpolated product. We characterized SST using three marine ecoregions in the California Current Ecosystem determined by Spalding et al. (2007) and applied by Satterthwaite et al (2019) and Gosselin et al. (2021). We calculated the seasonal mean SST across coastal northern California, coastal Oregon, coastal Washington, and Salish Sea ecoregions and standardized each seasonal SST with a mean of 0 and standard deviation of 1. Summer included SST during June, July, and August; winter included SST during January, February and March.

Seasonal means are one important characterization of the marine environment impacting juvenile salmon, but extreme environmental anomalies and variability are an important driver that can also impact salmon survival (Sharma et al. 2013). Recently, the California Current Ecosystem has experienced frequent and severe marine heatwave (MHW) events. We used three indicators that represent intensity, size, and persistence of MHWs. Warm SST events are considered a heatwave when SST anomalies reach the 90th percentile of a 30 year mean for at least 5 days (Hobday et al. 2016). MHW intensity is the SST anomaly once SST has reached heatwave status. MHW cover is the percent coverage of the ocean area within the EEZ that is in heatwave status. Finally, MHW degree day characterizes how long and intense a heatwave is as the cumulative degree days that SST is at or above the long-term mean (base temperature of 0). MHW indices are from NOAA SWFSC Environmental Research Data Services and use Multi-scale Ultra-high Resolution (MUR) SST Analysis Anomaly to derive indices.

Spring Transition Index (STI) and Total Upwelling Magnitude Index (TUMI) are two descriptors of the upwelling seas (Bograd et al. 2009) that influence primary production and forage availability in the northern California Current (Hickey and Banas 2008). STI refers to the timing of onset of the upwelling season and is represented by the date (Julian Day) on which the cumulative upwelling reaches its minimum value and positive upwelling prevails. TUMI represents total upwelling throughout the upwelling season and is the cumulative upwelling from the start date of the STI to the observed end date of the upwelling season. Upwelling data was available from 33°N to 48°N at 3-degree intervals. Upwelling in 45°N aligns with ecoregion 3 (coastal Oregon) and 48°N aligns with ecoregion 2 (coastal Washington); STI and TUMI are highly correlated (Pearson's correlation coefficient 0.75 and 0.72 respectively) across these locations. As a result, we used an average STI and TUMI across 45°N and 48°N for all stocks and standardized these annual indices such that it had a mean of 0 and standard deviation of 1.

Horizontal ocean transport can influence the dynamics of higher-trophic-level species in coastal ecosystems by altering either physical oceanographic conditions or the advection of food resources into coastal areas (Malick et al. 2017). In coastal Washington and British Columbia, the north-south location of the North Pacific Current bifurcation strongly influences productivity of Pacific salmon species (Malick et al. 2017). We used the bifurcation index developed by Malick et al. (2017) as an indicator of transport relevant to Pacific salmon. This index ranges from 0–1 where higher values indicate northern bifurcation and lower values indicate further south.

Freshwater predictor variables

Smolts are highly vulnerable during their downstream migration (Healey 1991), and river flow has been found to be positively correlated with survival (Notch et al., 2020). For each hatchery, we identified the nearest downriver U.S. Geological Survey (USGS) gauge station with time series data on river flow (cubic feet per second; CFS, Summary Table 2). For each program, expert opinion was used to determine months when river flows were most likely to influence smolt survival, and average flow (CFS) during these months was used as a predictor variable.

Hatchery predictor variables

Variables related to size or number of fish released may help assess density dependence, while variables related to timing of release may help determine optimal environmental conditions during juvenile rearing. We incorporated total number of fish released annually and, when available, average size of fish at release (weight in grams, fish per pound) and the calendar day or month of release. Size at release and release timing were available for all programs where analysis was based on CWT data.

Statistical modeling

Stocks included in this analysis have different run and return timing and, as a result, they experience freshwater and early marine environmental conditions during different seasons based on their migratory timing. Therefore, we modeled the effects of predictor variables on SARs from each stock independently and did not consider hierarchical modeling approaches or shared trends. Our approach allows for stock-specific characterizations of environmental conditions that account for each stock's life history strategy.

For each stock, we constructed a series of Generalized Additive Models (GAMs), using the mgcv package in R (R Core Team 2024) which allows for non-linear relationships between predictor variables and responses (Wood 2011). Each GAM modeled the response with a binomial family (logit link). We used the binomial family to model SARs based on the releases and returns each year, rather than model the derived SAR (e.g. total returns/total release)—this approach incorporates variation in the total number released each year such that years with more data get more weight (our approach weights each individual fish equally). To avoid overfitting and comparing millions of models, we limited the potential number of predictor variables included in each model to 2–4 variables. Similarly, we constrained the wiggliness of each relationship by setting the dimensionality of the basis expansion at 3 for each predictor variable (essentially allowing for curves to be no more complicated than quadratic shapes). Flow during outmigration can be an influential driver of juvenile survival (Petrosky and Schaller 2010) and was included in all models when applicable (e.g., flow was not incorporated for one stock with a very short migration to the sea; Summary Table 2).

Because our modeling approach was performed separately for each stock, selection of predictor variables was also conducted independently by stock. As an initial covariate screening, we fit a series of GAMs to SAR data for each stock using a single predictor variable. We then excluded predictor variables with ecologically unrealistic relationships with SAR data. Specifically, we removed predictor variables for which the relationship with SARs was concave up, which represents estimated SAR rates would be highest at extreme low and high values of a predictor (e.g. highest survival at low and high temperatures). Next, we constructed a list of all potential combinations of 1–3 predictor variables from the retained list and added flow as a predictor in each potential model, resulting in a list of potential permutations of 2–4 predictor variables. For each candidate model, we calculated two measures of data support and fit: Akaike’s Information Criterion (AIC; Akaike 1973) and Root Mean Squared Error (RMSE) as a measure of predictive accuracy.

Quantifying predictor variable importance

For each stock, we quantified the marginal mean improvement in RMSE and AIC corresponding to each predictor variable across models. We adopted this approach instead of looking at the single best model (lowest RMSE or AIC) because for a given stock there were many models that were able to produce similar fits to the data. Our aim was to identify predictors that consistently contributed to lower RMSE or AIC across models (despite changes in the inclusion or exclusion of correlated predictors), which suggests that those covariates contain unique, meaningful information. For each predictor variable, we used RMSE to evaluate how much predictive capacity increased by inclusion of that predictor variable across models with that predictor. For each potential predictor variable considered in models with *m* predictor variables, we used the set of *n* models with *m* - 1 predictor variables without that predictor as a baseline, and for each calculated the average change in RMSE,

$$p_i = \frac{1}{n}\sum_{j=1}^{n}\frac{RMSE_{j,m-1} - RMSE_{j,m}}{RMSE_{j,m-1}}$$

Where $RMSE_{j,m-1}$ might represent RMSE from a model with 2 predictors, and $RMSE_{j,m}$ would represent the RMSE statistic for the same model, with the predictor variables of interest added (3 predictor variables total). In other words, p_i represents the average improvement in RMSE gained from adding variable X to a model that already has 2 predictor variables. To calculate the mean marginal improvement across models with differing numbers of predictor variables, we calculated the average $\sum_{i=1}^{3} p_i/3$ for each predictor variable (Ward et al. 2024). For visualization purposes, we constructed models for each stock using the predictor variables with the highest average improvement in RMSE.

As a second approach, we calculated the estimated effect sizes for each predictor variable. Estimating effect sizes with GAMs is slightly more complicated than linear models because relationships can be non-linear and asymmetric around the mean. We estimated the average absolute effect size for all marine predictor variables by holding all other predictor variables at their respective means, and evaluating the average change in survival that would result from the predictor variables of interest being decreased or increased by 1 standard deviation. Predictor variables were then ranked in descending order, corresponding to those with the largest to smallest effect sizes.

Calculating trends in SARs

To assess trends in the SAR data—independent of environmental predictor variables—we used dynamic generalized linear models to quantify change through time. Each of our SAR datasets was used to generate a binomial response (total number of releases, total number of returns) for each brood year. We estimated an initial intercept B_0 for the starting year of each time series and treated the trend as a latent random walk $u_t \sim N(u_{t-1}, \sigma)$. We used a binomial distribution (logit link) to relate the observed data with the estimated survival rates $logit(p_t) = B_0 + u_t$; in this framework, the u_t represents a change in log-odds between time steps (negative values correspond to decreases in SAR rates). For each stock we summarized the long-term (average differences of u_t across all years) and average 5-year short-term trend (average differences of u_t over the last 5 years of data). All models were constructed using Stan (Stan Development Team

2024a) and run through R using rstan (R Core Team 2024; Stan Development Team 2024b). We ran 4 parallel chains of 3000 iterations (using the first 50% for burn-in) and ensured all models were free of divergent transitions and had maximum Rhat values < 1.1.

Approach for qualitative vulnerability assessment

Our qualitative climate vulnerability analysis was a modification of the analytical structure developed by Crozier et al. (2019), which used expert opinion to score key environmental exposures that different salmon and steelhead evolutionarily significant units (ESUs) are expected to experience in a changing climate. For our assessment, we modified the list of environmental variables to only include those pertinent to life stages when hatchery fish are outside the hatchery environment (based on expert opinion). We recognize that climate change can also have impacts within the hatchery environment, but assessing these impacts requires facility-specific analyses (e.g., Hanson and Peterson 2014) that were beyond the scope of this assessment. Furthermore, vulnerability to environmental attributes that affect fish during early life history stages will depend on whether potential mitigation measures are implemented at a hatchery facility.

For our assessment, environmental variables were categorized in two groups: a sensitivity group, and an exposure group. Sensitivity was assessed using environmental factors such as estuary stage, marine stage, adult freshwater stage, other stressors, and ocean acidification, while excluding less relevant attributes like early life history, juvenile freshwater stage, cumulative life-cycle effects, hatchery influence, and population viability. The exposure metric was scored based on hydrologic regime, sea level rise, sea surface temperature, ocean acidification, upwelling, and ocean currents. Attributes like stream temperature, summer water deficit, and flooding were excluded because there is greater potential to mitigate their effects with hatchery infrastructure and operations. For the retained scoring attributes, we maintained the numerical values assigned by Crozier et al. (2019) and applied their logic rule for ranking the sensitivity and exposure components. Climate sensitivity and exposure scoring was done by Species Management Unit (SMU), which ODFW defines as a collection of populations from a common geographic region that share similar genetic and ecological characteristics. SMUs often align geographically with federal ESUs but are separated into run types (e.g. spring and fall Chinook) that may be combined in an ESU. For SMUs that did not align with an ESU that was evaluated by Crozier et al. (2019), we either used another source that used similar methods (ODFW 2021) or relied on information from a neighboring ESU. For several SMUs, no appropriate analog was available, and climate vulnerability could not be assessed. The final vulnerability score for each SMU was calculated as the product of the exposure and sensitivity scores.

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Summary Tables

Summary Table 1 Summary of marine indicators used for modeling smolt to adult returns (SARs) across hatchery stocks.

Indicator	Summary timeline	Scale	Description	Hypothesized relationship
Spring Transition Index (STI)	annual	global	The date (Julian Day) on which the Cumulative Upwelling Index (CUI) reaches its minimum value and positive upwelling prevails.	Negative
Total Upwelling Magnitude Index (TUMI)	annual	global	Total CUI from the start date of the STI to the observed end date of the upwelling season.	Positive
North Pacific Current Bifurcation Index	annual	regional	Interannual variability in the latitude of the North Pacific Current bifurcation as well as the volume of water that bifurcates northward into the Alaska Current and southward into the California Current (Malick et al. 2016). Positive values are associated with increased NPC strength, a northward-shifted bifurcation, and increased transport into the California Current.	Positive
North Pacific Gyre Oscillation (NPGO)	seasonal	basin	Pattern of sea surface height variability which provides a strong indicator of ecosystem dynamics including salinity and phytoplankton concentrations.	Positive
Pacific Decadal Oscillation (PDO)	seasonal	basin	Warm or cool phase climate pattern where changes in temperature and salinity affect species dynamics and distribution.	Negative
Marine Heat Wave Degree Day	seasonal	regional	Expresses how long and intense a heatwave is. Calculated by averaging the points within a region (in this case the US Exclusive Economic Zone, or EEZ) where the Sea Surface Temperature Anomaly (SSTa) is greater than 0 (i.e.. above the 30-year average).	Negative
Marine Heat Wave Intensity	seasonal	regional	Spatial average intensity where average SSTa for all cells in a given area (in this case the EEZ) exceed the heatwave threshold of 1.29 (interpreted as the 90th percentile above the long-term mean).	Negative

Marine Heat Wave Cover within the US Exclusive Economic Zone (US EEZ)	seasonal	regional	Percent coverage of ocean area within the EEZ that is in 'heatwave status' (where SSTa exceeds 1.29) on a given day. Expresses how large a heatwave is near the coast.	Negative
Sea Surface Temperature (SST)	seasonal	regional	Average monthly sea surface temperatures recorded across coastal ocean ecoregions 1-4 of the California Current Ecosystem (Gosselin et al. 2021).	Parabolic
Ocean Station Papa SST	seasonal	regional	SST measured at a long-term ocean climate measurement site located at 50°N, 145°W.	Parabolic
SST Arc	seasonal	regional	The scaled anomalies of SST within the NE Pacific Arc (Johnstone and Mantua, 2013).	Negative

Summary Table 2 Summary of stocks used for analysis with life history and freshwater predictor variable details (RMIS = Regional Mark Information System; LSRCP = Lower Snake River Compensation Plan; HMS = Hatchery Management System).

Program	USGS Station	CFS details	Brood Years	Release dates	Release date as model predictor	Avg. size as model predictor	Life History Details	Data Sources for SAR Analysis
				Spring Chinook				
Trask	Wilson River in Tillamook (14301500)	Average August CFS	1986–2017	Jul–Sep	Month	Y	Released as subyearlings. Adults return Apr–Jun, recovered hatchery Aug–Oct (3–6 y.o.). Segregated stock.	RMIS
Deschutes (Round Butte)	Deschutes near Biggs (14103000)	Average May CFS	1990–2016	Apr–Jun	Month	Y	Released as yearlings. Adults return Mar–Jul, recovered hatchery May–Oct (3–6 y.o.). Integrated stock.	RMIS
McKenzie	Columbia Dalles (113459)	Average April CFS	1981–2016	Jan–Mar	Month	Y	Released as yearlings. Adults return Feb–Jul, recovered hatchery May–Oct (3–6 y.o.). Integrated stock.	RMIS
Imnaha	Columbia Dalles (113459)	Average April CFS	1984–2016	Mar–Apr	Avg. Julian day	Y	Released as yearlings. Adults return May–Jul, recovered hatchery Jul–Sep (3–5 y.o.). Integrated stock.	ODFW LSRCP summary
Rogue (Cole Rivers)	Rogue Grants Pass (14361500)	Average September CFS	1988–2017	Aug–Oct; Mar	Month	Y	Released primarily as subyearlings. Adults return Mar–Jun, recovered hatchery Apr–Sep (3–6 y.o.). Integrated stock.	RMIS
				Fall Chinook				
Salmon River	Siletz (14305500) as proxy	Mean August	1982–2017	Aug	N	Y	Released as subyearlings, short migration to ocean (~4 miles). Adults return Aug–Oct, recovered hatchery Sept–Nov (3–6 y.o.). Integrated Stock.	RMIS
Elk River	NA	NA	1981–2016	Oct–Nov; Feb	N	Y	Released primarily as subyearlings, short migration to ocean (~14 miles). Adults return Sep–Jan, recovered hatchery Oct–Jan (3–6 y.o.). Integrated stock.	RMIS
Big Creek	Columbia Dalles (113459)	Mean April	1986–2017	Mar–May	N	Y	Released as subyearlings, may rear in estuary for a time. Adults return Aug–Oct, recovered hatchery Aug–Oct (3–6 y.o.). Segregated stock.	RMIS

Program	USGS Station	CFS details	Brood Years	Release dates	Release date as model predictor	Avg. size as model predictor	Life History Details	Data Sources for SAR Analysis
				Coho				
Rogue (Cole Rivers)	Rogue Grants Pass (14361500)	Average April CFS	1981–2016	Apr–Jul	Avg. Julian day	N	Released as yearlings. Adults return Sep–Dec (3 y.o.). Integrated stock.	RMIS
Big Creek	Columbia Dalles (113459)	Average April CFS	1981–2016	Apr–May	Avg. Julian day	N	Released as yearlings. Adults return Sep–Dec (3 y.o.). Segregated stock.	RMIS
Sandy	Columbia Dalles (113459)	Average April CFS	1981–2016	Apr–May	Avg. Julian day	N	Released as yearlings. Adults return Sep–Dec (3 y.o.). Segregated stock.	RMIS
				Summer steelhead				
Siletz	Siletz (14305500)	Average April CFS	1992–2016	Apr	N	N	Released as yearlings. Adults return Apr–Aug, caught Jun–Nov (primarily 2–4 y.o.). Segregated stock.	ODFW HMS; harvest estimates; unpublished trap and age data
Rogue (Cole Rivers)	Rogue Grants Pass (14361500)	Average April CFS	1993–2016	Apr–May	N	N	Released as yearlings. Return Apr–Oct, recovered at hatchery May–Nov (early and late runs, primarily 3–4 y.o.). Integrated stock.	ODFW HMS; harvest estimates; unpublished age data
Deschutes (Round Butte)	Deschutes near Biggs (14103000)	Average April CFS	2003–2016	Apr	N	N	Released as yearlings. Return Jun–Sep, recovered at hatchery Oct–Mar (primarily 2–3 y.o.). Segregated stock.	ODFW HMS; harvest estimates; unpublished trap data
Wallowa	Columbia Dalles (113459)	Average April CFS	1986–2016	Apr–May	N	N	Released as yearlings. Adults recovered at hatchery Feb–Jun (peak collection Mar–Apr). Segregated stock.	ODFW LSRCP summary
				Winter steelhead				
North Fork Nehalem	Nehalem at Foss (14301000)	Average April CFS	1993–2016	Mar–Apr	N	N	Released as yearlings. Adults return Dec-Apr (primarily 3-4 y.o.). Segregated stock (recently portion of program converted to integrated).	ODFW HMS; harvest estimates; unpublished age data
Alsea	Alsea at Tidewater (14306500)	Average April CFS	1993–2016	Apr–May	N	N	Released as yearlings. Adults return Dec-Apr (primarily 3-4 y.o.). Includes segregated and integrated stocks.	ODFW HMS; harvest estimates; unpublished age data

Summary Table 3 Predictor variables with top two ranked Root Mean Squared Error (RMSE) for each hatchery stock. The number next to each variable represents its rank.

Species	Program	Predictor variable
Spring Chinook	Trask	1 - Total released
		2- SST summer
	Deschutes (Round Butte)	1 - SST summer L1
		2- PDO summer L1
	McKenzie	1 - SST summer L1
		2- PDO summer L1
	Imnaha	1 - PDO summer L1
		2- PDO summer
	Rogue (Cole Rivers)	1 - MHW intensity summer
		2- TUMI
Fall Chinook	Salmon River	1 - STI L1
		2- SST Arc summer
	Elk River	1 - Average weight
		2- NPGO winter L1
	Big Creek	1 - NPGO winter L1
		2- SST summer
Coho	Rogue (Cole Rivers)	1 - SST winter L1
		2- Average weight
	Big Creek	1 - PDO summer L1
		2- MHW intensity summer
	Sandy	1 - PDO summer L1
		2- Total released
Summer Steelhead	Siletz	1 - NPGO summer
		2- NPGO summer L1
	Rogue (Cole Rivers)	1 - SST winter L1
		2- SST Arc winter L1
	Deschutes (Round Butte)	1 - NPGO summer L1
		2- NPGO winter L1
	Wallowa	1 - Total released
		2- NPGO summer
Winter Steelhead	Nehalem	1 - STI L1
		2- NPGO summer
	Alsea	1 - Total released
		2- STI L1

Summary Table 4 Average long term and short term (5-year) trends in smolt to adult returns (SARs) with their 95% credible intervals. Trends are starred (*) where the credible intervals do not cross zero.

Species	Program	Trend	Mean	SD	2.50%	97.50%
Spring Chinook	Trask	long term *	-0.019	0.002	-0.022	-0.016
		short term *	0.043	0.021	0.002	0.085
	Deschutes (Round Butte)	long term *	-0.097	0.002	-0.101	-0.094
		short term *	-0.426	0.018	-0.461	-0.392
	McKenzie	long term *	-0.056	0.001	-0.057	-0.054
		short term *	-0.129	0.007	-0.143	-0.114
	Imnaha	long term	-0.004	0.003	-0.009	0.002
		short term *	-0.166	0.008	-0.181	-0.151
	Rogue (Cole Rivers)	long term *	-0.109	0.001	-0.110	-0.107
		short term *	-0.091	0.008	-0.107	-0.075
Fall Chinook	Salmon River	long term *	-0.008	0.001	-0.011	-0.005
		short term *	-0.086	0.006	-0.098	-0.075
	Elk River	long term *	0.015	0.001	0.014	0.017
		short term *	-0.103	0.004	-0.111	-0.094
	Big Creek	long term	-0.002	0.002	-0.005	0.001
		short term *	0.21	0.015	0.181	0.24
Coho	Rogue (Cole Rivers)	long term *	-0.063	0.004	-0.072	-0.055
		short term *	-0.289	0.043	-0.374	-0.207
	Big Creek	long term *	-0.010	0.001	-0.013	-0.008
		short term *	0.065	0.01	0.045	0.085
	Sandy	long term *	-0.037	0.002	-0.041	-0.034
		short term *	-0.088	0.02	-0.128	-0.049
Summer Steelhead	Siletz	long term *	-0.015	0.002	-0.018	-0.011
		short term *	-0.304	0.009	-0.322	-0.287
	Rogue (Cole Rivers)	long term *	-0.029	0.001	-0.030	-0.028
		short term *	-0.048	0.004	-0.056	-0.040
	Deschutes (Round Butte)	long term *	-0.050	0.002	-0.053	-0.046
		short term *	-0.079	0.006	-0.090	-0.068
	Wallowa	long term *	-0.031	0.001	-0.033	-0.030
		short term *	-0.366	0.005	-0.377	-0.356
Winter Steelhead	Nehalem	long term	-0.001	0.001	-0.004	0.002
		short term *	-0.417	0.007	-0.431	-0.403
	Alsea	long term *	-0.011	0.001	-0.013	-0.009
		short term *	-0.133	0.005	-0.143	-0.122

Summary Table 5a Logic rule used to assign exposure, sensitivity, and cumulative vulnerability rankings to assessed hatchery programs. This vulnerability scoring process was derived from Crozier et al. (2019), where the sensitivity and exposure of specific salmon and steelhead stocks were expertly ranked using a set of environmental attributes. Specific environmental attributes were considered ‘exposure attributes’ while others were considered ‘sensitivity attributes.’ The overall sensitivity and exposure of each stock was assigned a numeric score based on the average score values of their environmental attributes (e.g. if there were >3 environmental attribute means within the sensitivity category with a value of ≥3.5, overall sensitivity was ranked as a 4 or ‘Very High’). The product of the overall sensitivity and exposure scores was then used to create a final cumulative vulnerability ranking for each stock. For our analysis, we removed attributes that were not as relevant to hatchery fish (e.g. hatchery influence) or that could be modified within the hatchery environment (e.g. stream temperature, summer water deficit). The remaining environmental attributes, which are expected to impact hatchery fish during life stages outside the hatchery, were used to score their levels of sensitivity, exposure, and cumulative vulnerability.

Overall sensitivity or exposure score	Numeric score	Logic rule
Very High	4	More than 3 attribute means ≥ 3.5
High	3	More than 2 attribute means ≥ 3
Moderate	2	More than 2 attribute means ≥ 2.5
Low	1	All other scores
Cumulative vulnerability	**Component product**	**Component combinations**
Very High	≥12	Very high/high or Very high/very high
High	8-11	Very high/moderate or High/high
Moderate	4-6	Very high/low, High/moderate, or Moderate/moderate
Low	≤3	High/low, Moderate/low, or Low/low

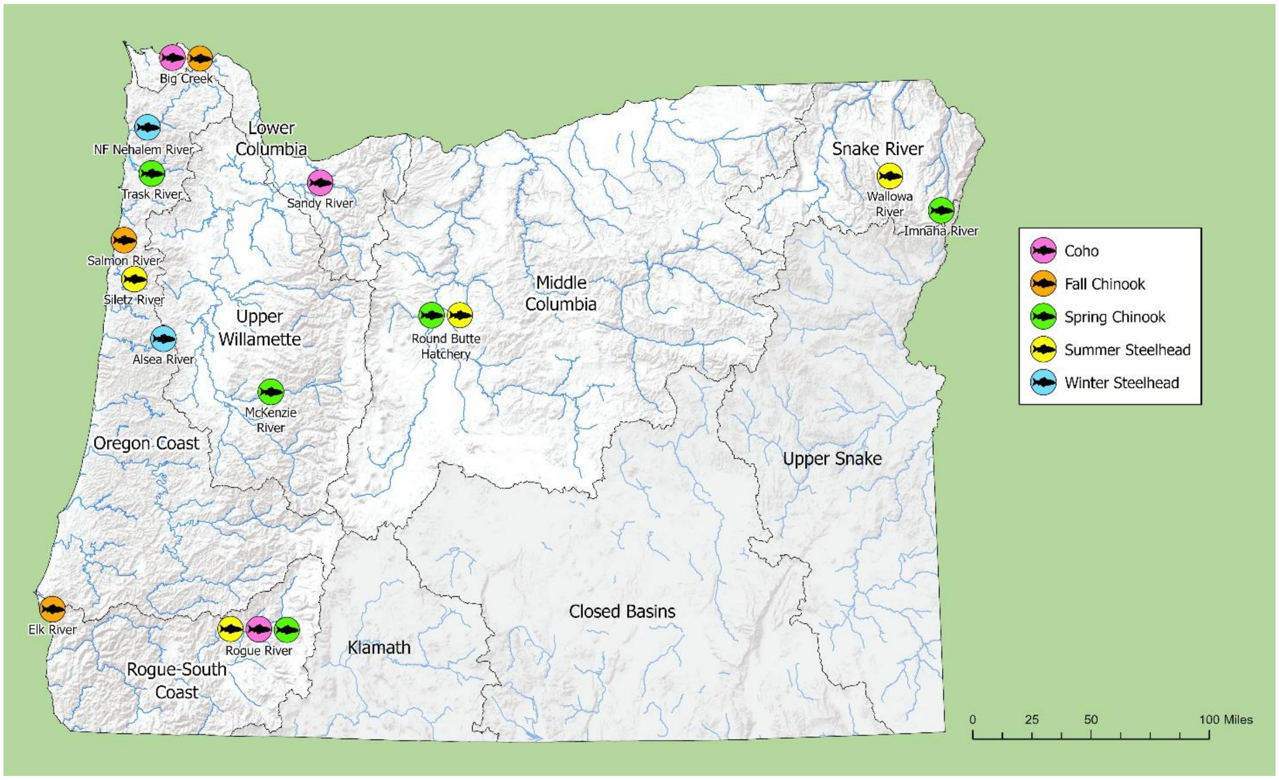
Summary Table 5b Final cumulative ranks for exposure, sensitivity, and vulnerability across Oregon Pacific salmon and steelhead Species Management Units (SMUs). Hatchery stocks included in our quantitative assessment are highlighted in bold. *SAFE = Select Area Fishery Enhancement Program.

Species	SMU	Programs	Exposure Score	Sensitivity Score	Vulnerability Score	ESU
Spring Chinook	Oregon Coast	**Trask**, Nestucca, North Umpqua	High	Low	Low	Based on Lower Columbia River Chinook (not run specific)
	Rogue–South Coast	**Rogue (Cole Rivers)**				NA
	Lower Columbia River	*SAFE, Sandy, Hood	High	Low	Low	Lower Columbia River Chinook (not run specific)
	Upper Willamette River	Clackamas, North Santiam, South Santiam, **McKenzie**, Middle Fork Willamette	High	High	High	Upper Willamette River (spring) Chinook
	Middle Columbia River	**Deschutes (Round Butte)**	High	High	High	Middle Columbia River spring-run Chinook
	Snake River	Catherine Creek, Upper Grande Ronde, Wallowa, **Imnaha**, Lookingglass Creek	High	High	High	Snake River spring/summer-run Chinook
Fall Chinook	Oregon Coast	Necanicum, Trask, Nestucca, **Salmon**, Umpqua, Coos, Coquille, **Elk**	High	Low	Low	Based on Lower Columbia River Chinook (not run specific)
	Rogue–South Coast	Chetco, Indian Creek (Rogue)				NA
	Lower Columbia River	**Big Creek**, Bonneville	High	Low	Low	Lower Columbia River Chinook (not run specific)
	Middle Columbia River	Umatilla				NA

Species	SMU	Programs	Exposure Score	Sensitivity Score	Vulnerability Score	ESU
Coho	Oregon Coast	North Fork Nehalem, Trask, South Umpqua	Moderate	Moderate	Moderate	Oregon Coast Coho
	Rogue–South Coast	**Rogue (Cole Rivers)**	High	Moderate	Moderate	Based on climate vulnerability assessment for coho salmon in the Rogue–South Coast Multi-Species Conservation and Management Plan (ODFW 2021). Used scores for the Upper Rogue population.
	Lower Columbia River	**Big Creek**, *SAFE, **Sandy**	Moderate	Moderate	Moderate	Lower Columbia River Coho
	Middle Columbia River	Umatilla				NA
Summer Steelhead	Oregon Coast	Wilson, Nestucca, **Siletz**, North Umpqua	High	Low	Low	Based on Lower Columbia River steelhead (not run specific)
	Rogue-South Coast	**Rogue (Cole Rivers)**	High	Moderate	Moderate	Based on climate vulnerability assessment for summer steelhead in the Rogue–South Coast Multi-Species Conservation and Management Plan (ODFW 2021). Used scores for the Upper Rogue population.
	Lower Columbia River	Clackamas, Sandy	High	Low	Low	Lower Columbia River steelhead (not run specific)
	Upper Willamette River	Upper Willamette	High	Low	Low	Upper Willamette River (winter) steelhead
	Middle Columbia River	**Deschutes (Round Butte)**, Umatilla	High	High	High	Middle Columbia River (summer) steelhead
	Snake River	**Wallowa**, Little Sheep Creek	High	High	High	Snake River Basin (summer) steelhead

Species	SMU	Programs	Exposure Score	Sensitivity Score	Vulnerability Score	ESU
Winter Steelhead	Oregon Coast	Necanicum, **North Fork Nehalem**, Wilson, Nestucca, Siletz, **Alsea**, Siuslaw, South Umpqua, Tenmile, Coos, North Fork/South Fork Coquille	High	Low	Low	Based on Lower Columbia River steelhead (not run specific)
	Rogue–South Coast	Chetco, Applegate, Rogue	High	Low	Low	Based on climate vulnerability assessment for winter steelhead in the Rogue–South Coast Multi-Species Conservation and Management Plan (ODFW 2021). Used average of scores for the Upper Rogue, Middle Rogue/Applegate, and Chetco populations.
	Lower Columbia River	Big Creek, Clackamas, Sandy	High	Low	Low	Lower Columbia River steelhead (not run specific)

Summary Figures



Summary Figure 1 Map of Oregon state with assessed hatcheries and hatchery stocks.

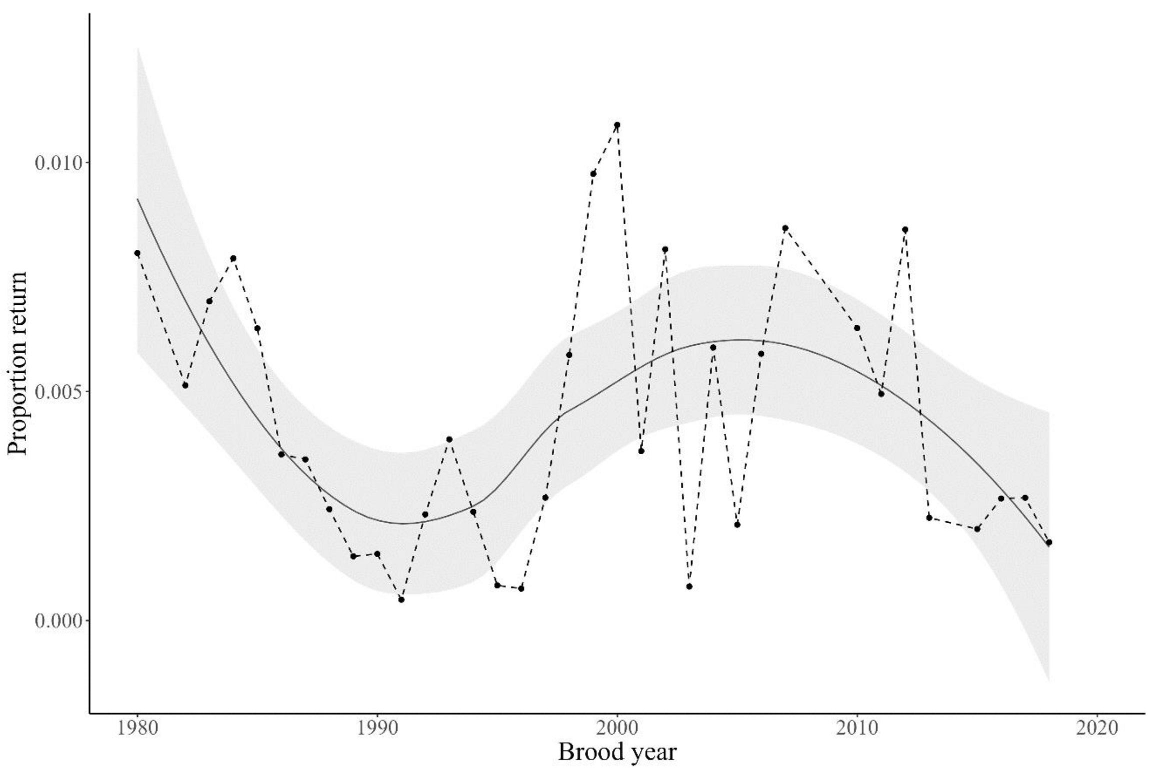
Stock Synthesis Tables and Figures

Spring Chinook Salmon

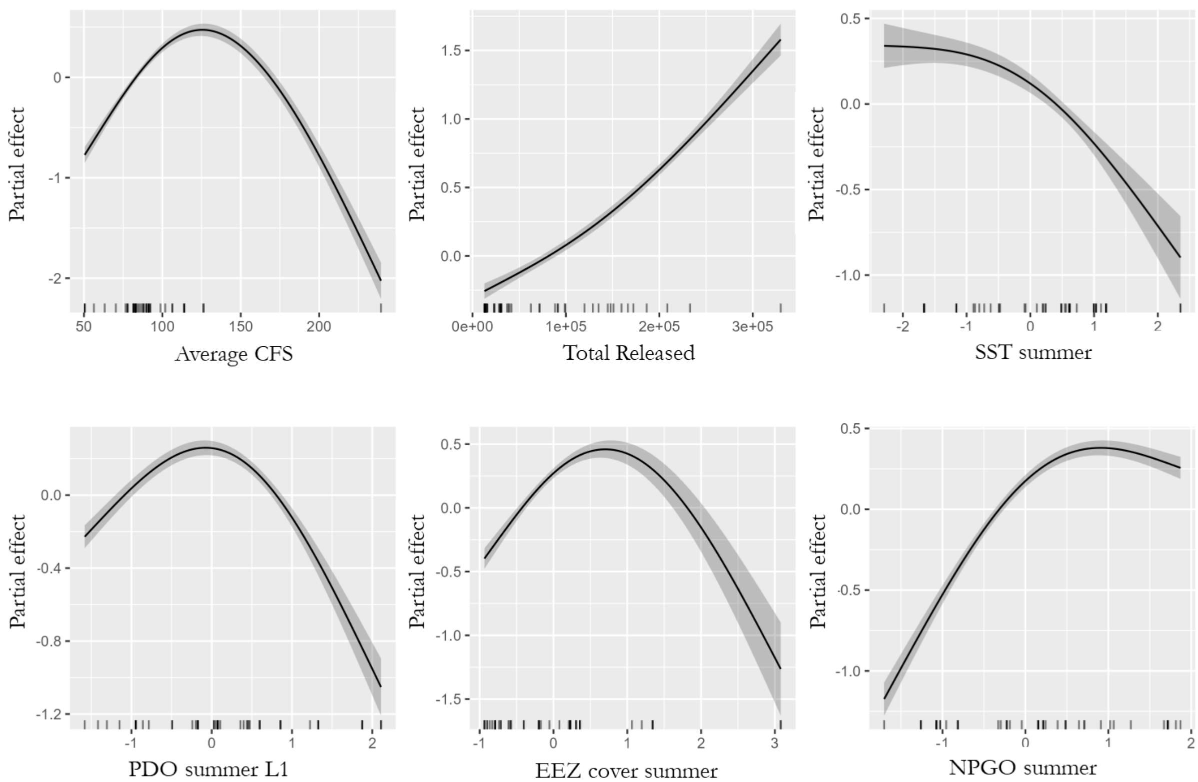
Trask

Synthesis Table 1.1 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Trask spring Chinook program.

Predictor	RMSE	AIC	Average absolute effect
Total released	0.7514	1827.76	0.0000
SST summer	0.8620	879.72	0.0011
PDO summer L1	0.8780	644.25	0.0012
EEZ cover summer	0.8930	689.89	0.0016
NPGO summer	0.9185	766.38	0.0017



Synthesis Figure 1.1 Estimated proportion of returning individuals, categorized by brood year, for the Trask spring Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

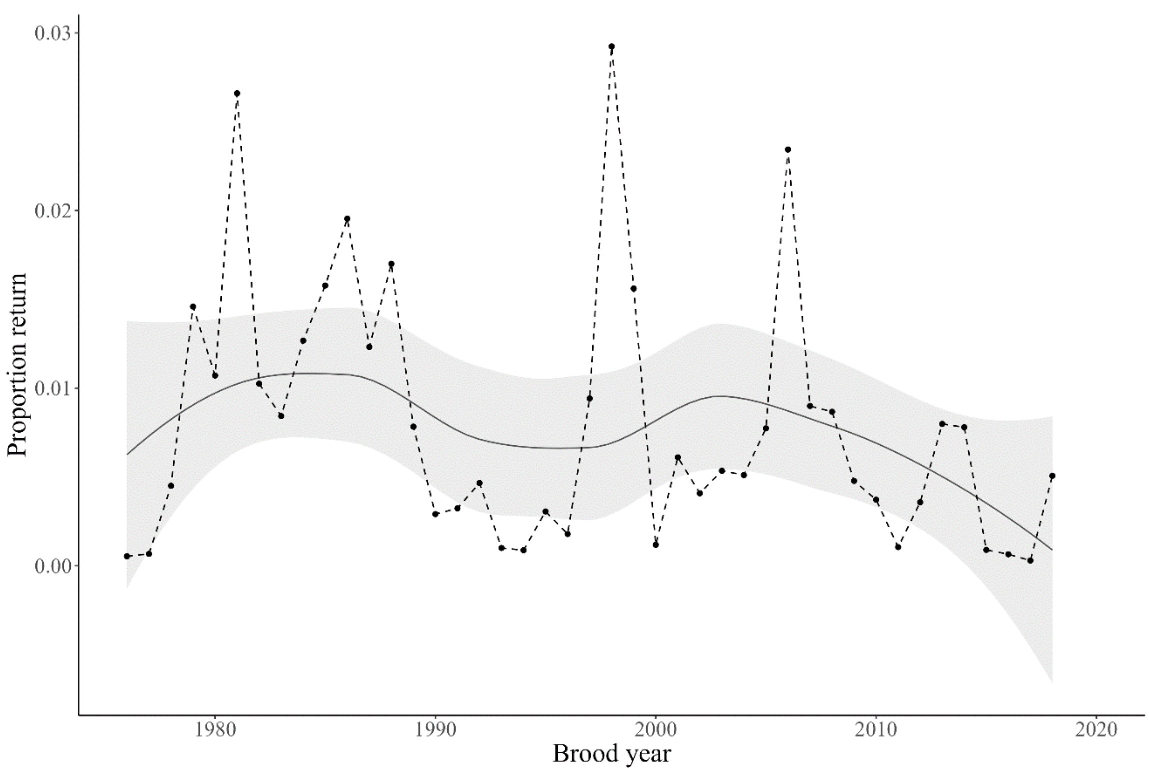


Synthesis Figure 1.11 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Trask spring Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

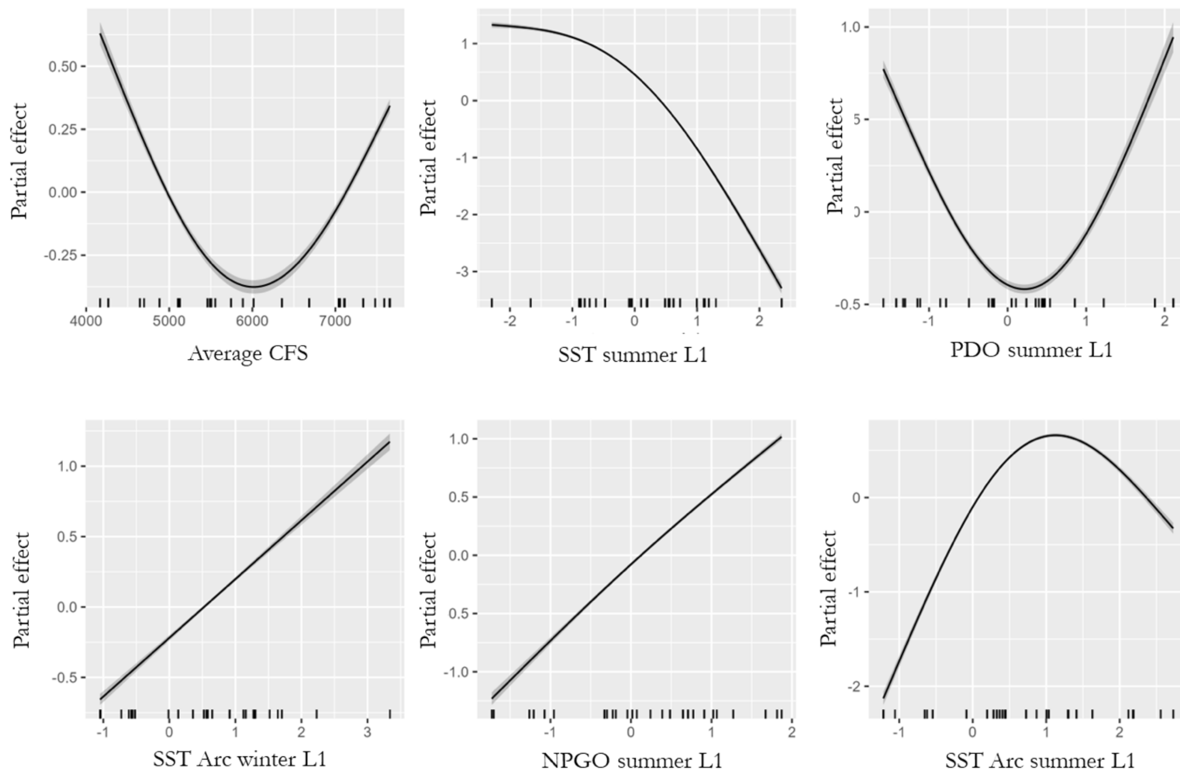
Deschutes (Round Butte)

Synthesis Table 1.2 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Deschutes (Round Butte) spring Chinook program.

Predictor	RMSE	AIC	Average absolute effect
SST summer L1	0.8358	12427.95	0.0018
PDO summer L1	0.8947	6912.02	0.0013
SST Arc winter L1	0.8991	8231.66	0.0009
NPGO summer L1	0.9037	10855.42	0.0014
SST Arc summer L1	0.9063	8154.87	0.0021



Synthesis Figure 1.2 Estimated proportion of returning individuals, categorized by brood year, for the Deschutes (Round Butte) spring Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

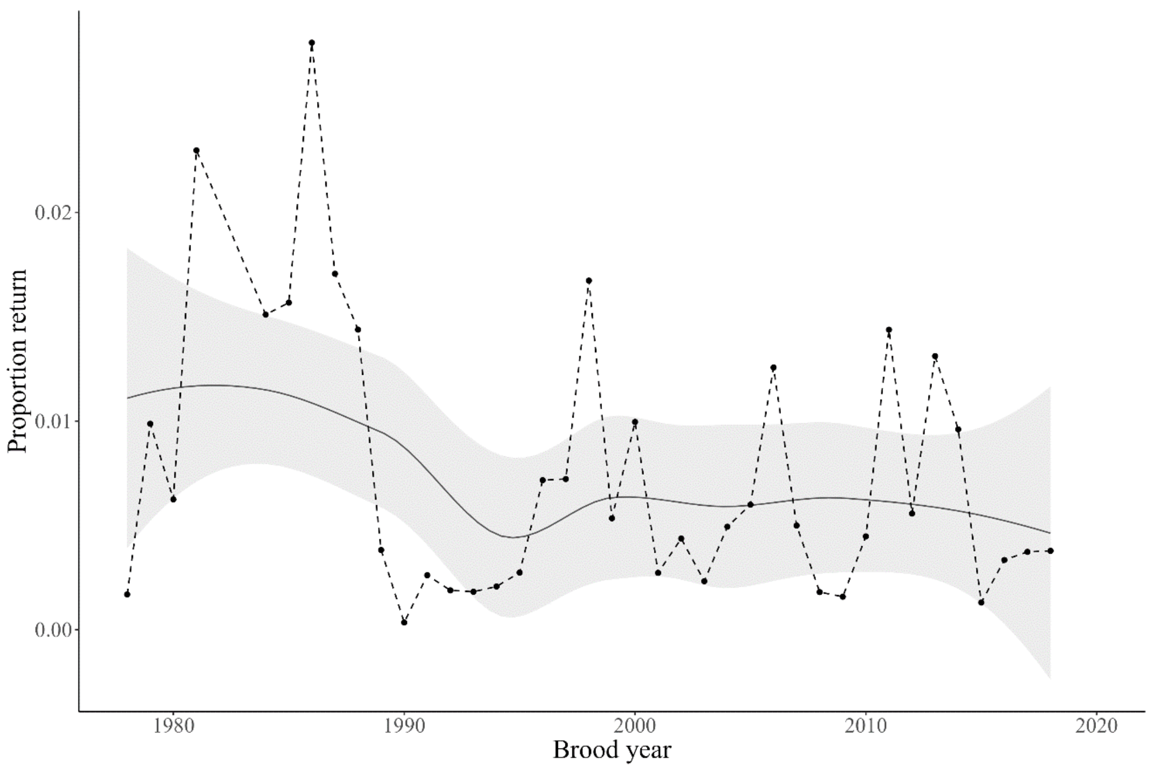


Synthesis Figure 1.21 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Deschutes (Round Butte) spring Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

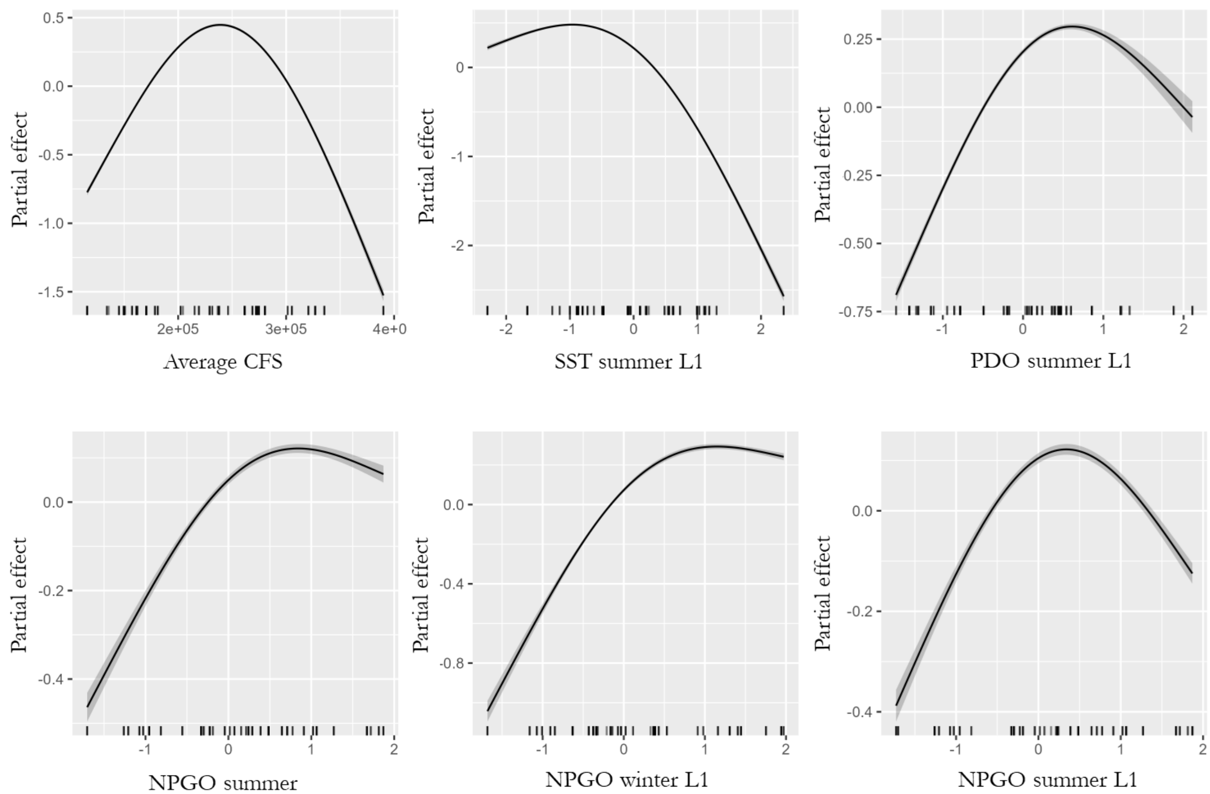
McKenzie

Synthesis Table 1.3 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the McKenzie spring Chinook program.

Predictor	RMSE	AIC	Average absolute effect
SST summer L1	0.9053	15355.95	0.0066
PDO summer L1	0.9264	12803.31	0.0034
NPGO summer	0.9290	11285.93	0.0023
NPGO winter L1	0.9297	10989.87	0.0051
NPGO summer L1	0.9465	7330.28	0.0018



Synthesis Figure 1.3 Estimated proportion of returning individuals, categorized by brood year, for the McKenzie spring Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

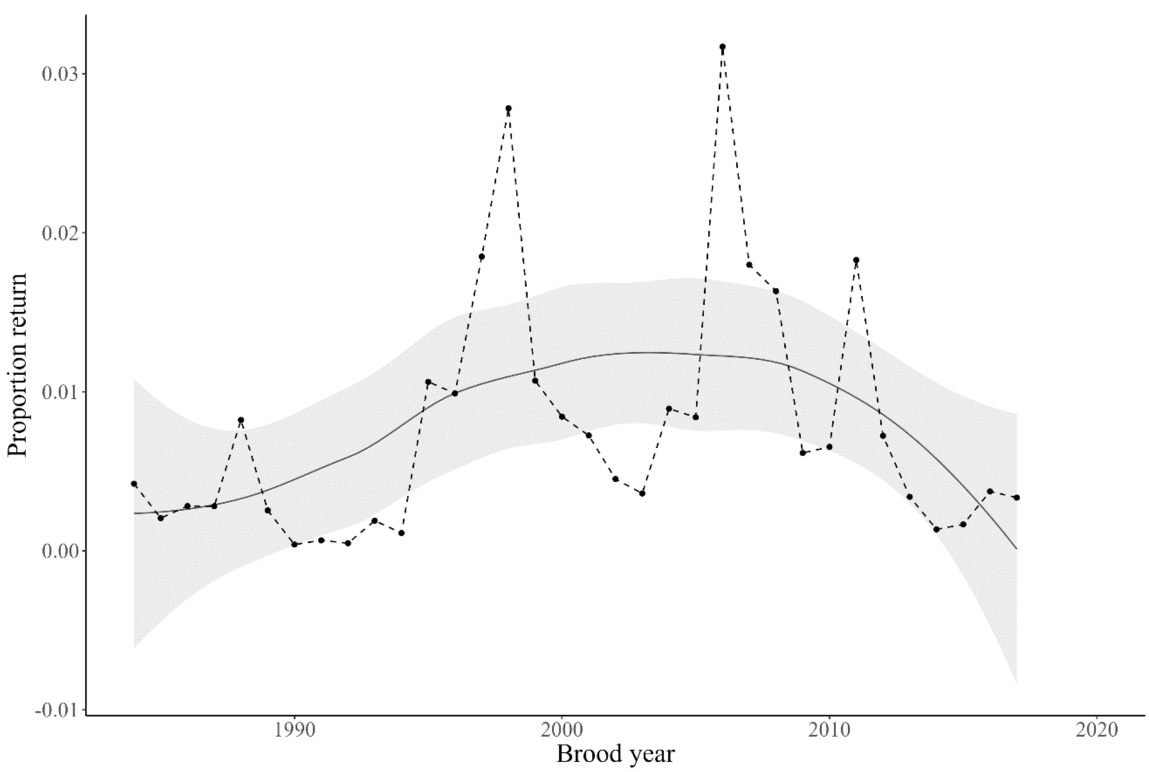


Synthesis Figure 1.31 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the McKenzie spring Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

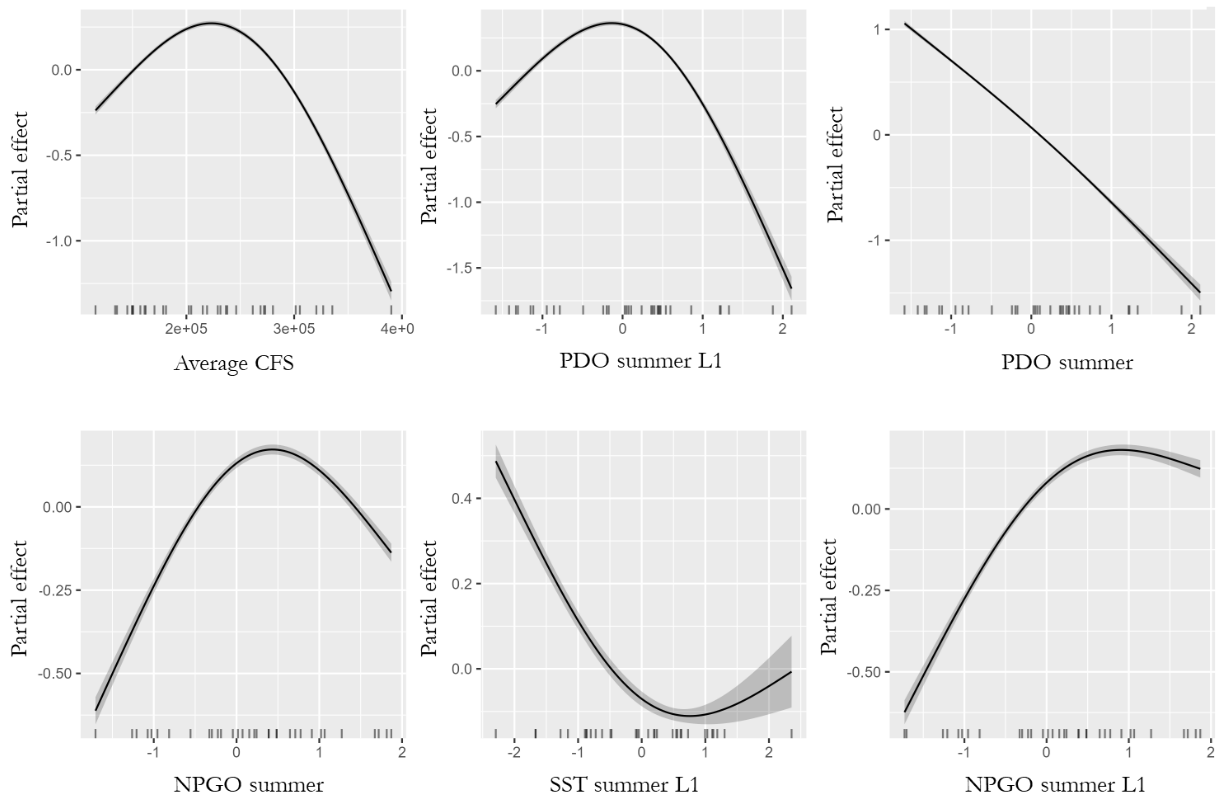
Imnaha

Synthesis Table 1.4 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Imnaha spring Chinook program.

Predictor	RMSE	AIC	Average absolute effect
PDO summer L1	0.8501	15171.64	0.0040
PDO summer	0.8506	25447.42	0.0080
NPGO summer	0.8509	15905.93	0.0019
SST summer L1	0.8849	10407.27	0.0014
NPGO summer L1	0.9034	16992.91	0.0023



Synthesis Figure 1.4 Estimated proportion of returning individuals, categorized by brood year, for the Imnaha spring Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

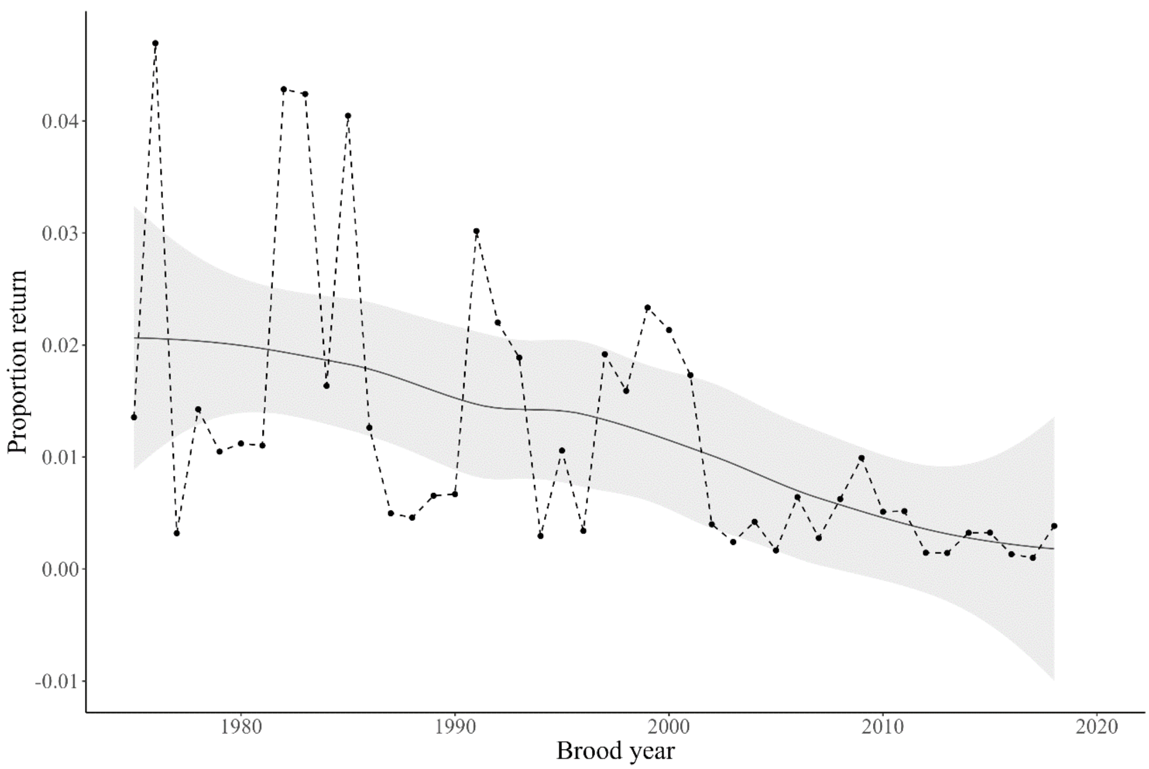


Synthesis Figure 1.41 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Imnaha spring Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

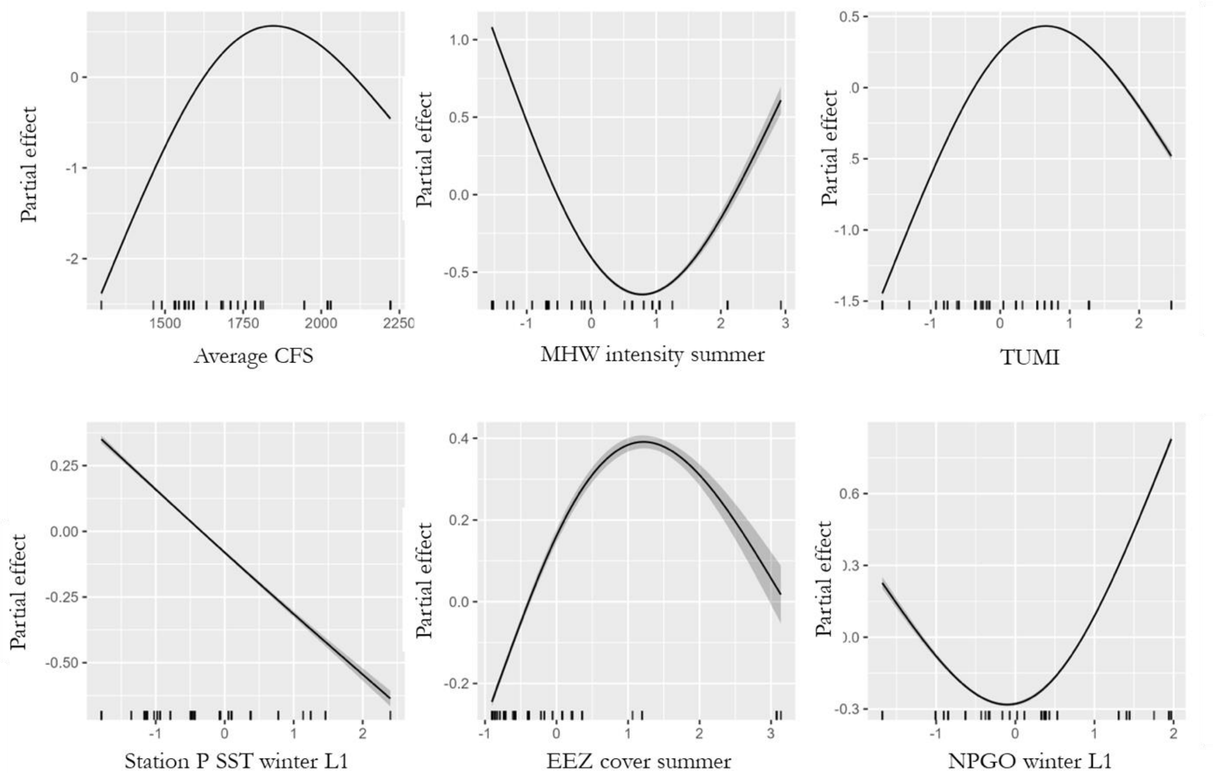
Rogue (Cole Rivers)

Synthesis Table 1.5 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Rogue (Cole Rivers) spring Chinook program.

Predictor	RMSE	AIC	Average absolute effect
MHW intensity summer	0.7600	62487.83	0.0058
TUMI	0.8608	58185.74	0.0027
Station P SST winter L1	0.8648	34098.32	0.0018
EEZ cover summer	0.8836	27171.64	0.0023
NPGO winter L1	0.9109	47301.06	0.0024



Synthesis Figure 1.5 Estimated proportion of returning individuals, categorized by brood year, for the Rogue (Cole Rivers) spring Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.



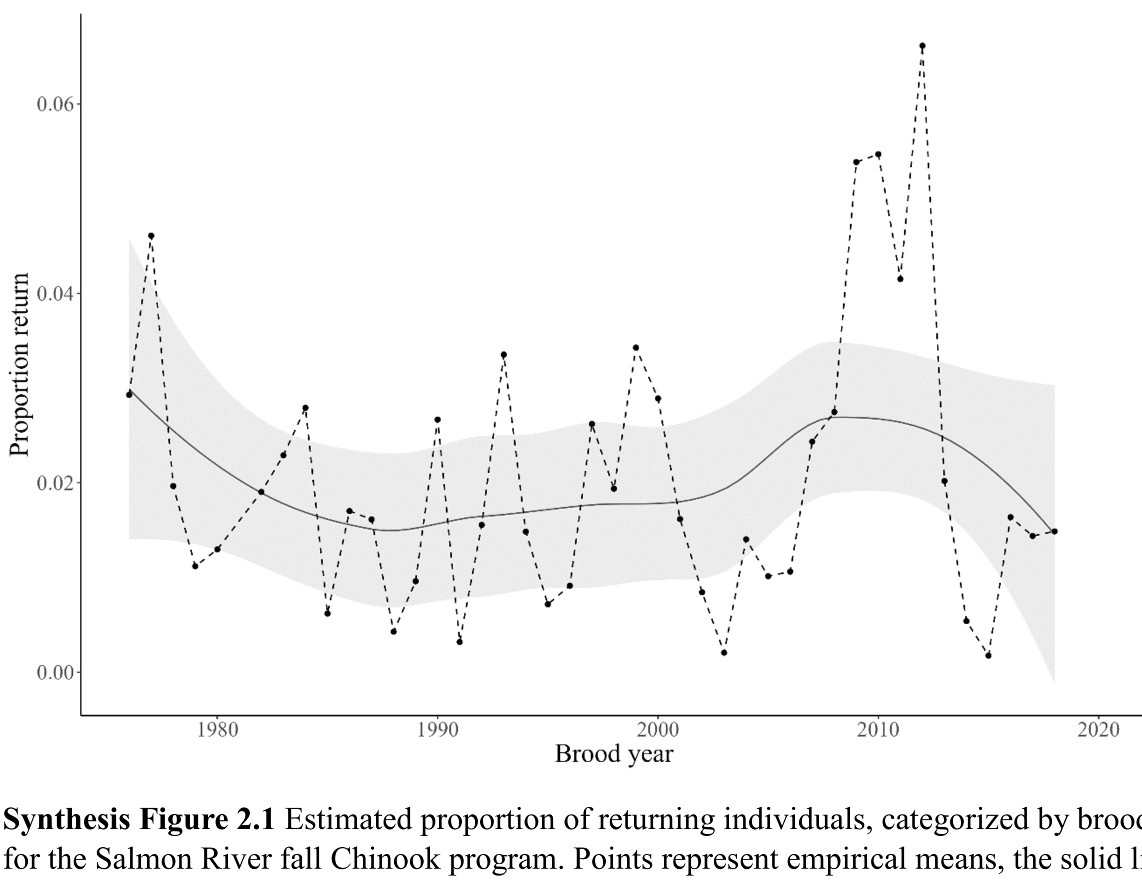
Synthesis Figure 1.51 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Rogue (Cole Rivers) spring Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

Fall Chinook Salmon

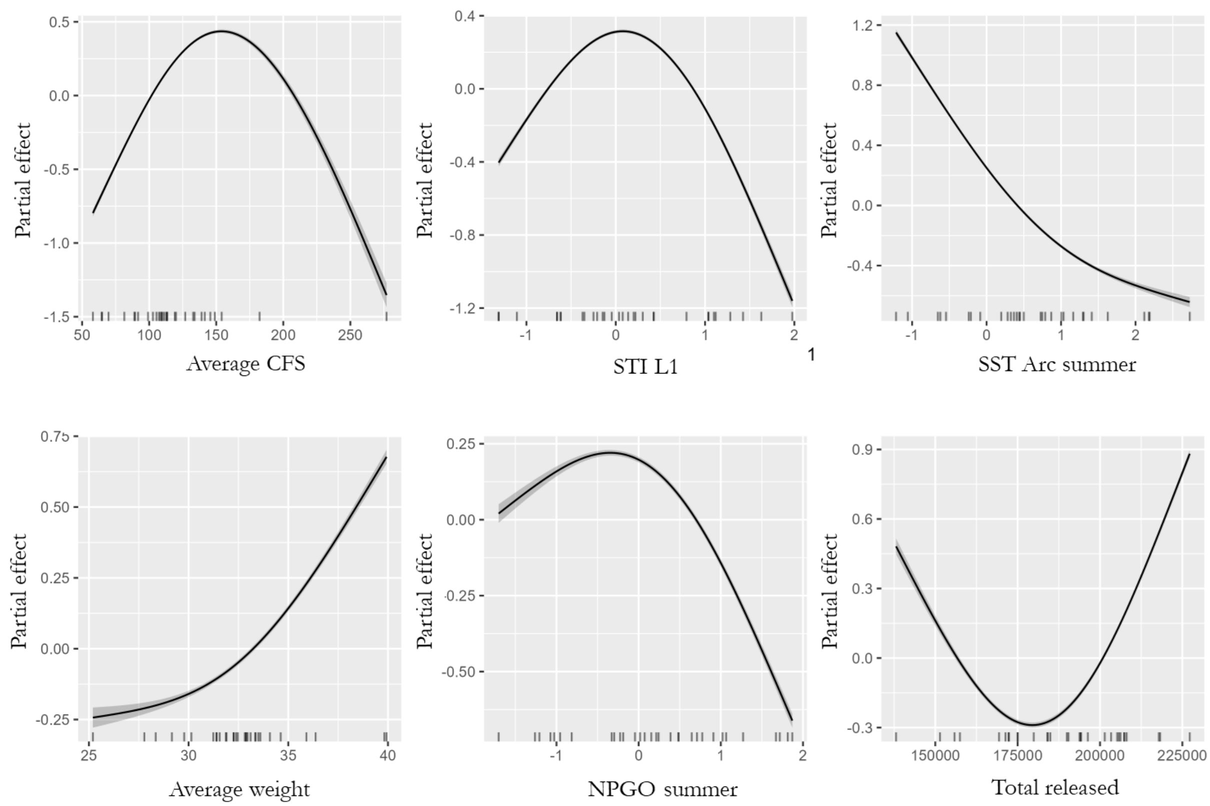
Salmon River

Synthesis Table 2.1 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Salmon River fall Chinook program.

Predictor	RMSE	AIC	Average absolute effect
STI L1	0.8954	5763.15	0.0944
SST Arc summer	0.9029	8180.55	0.1121
Average weight	0.9248	5308.78	0.0025
NPGO summer	0.9435	4750.21	0.0385
Total released	0.9451	4975.40	0.0000



Synthesis Figure 2.1 Estimated proportion of returning individuals, categorized by brood year, for the Salmon River fall Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

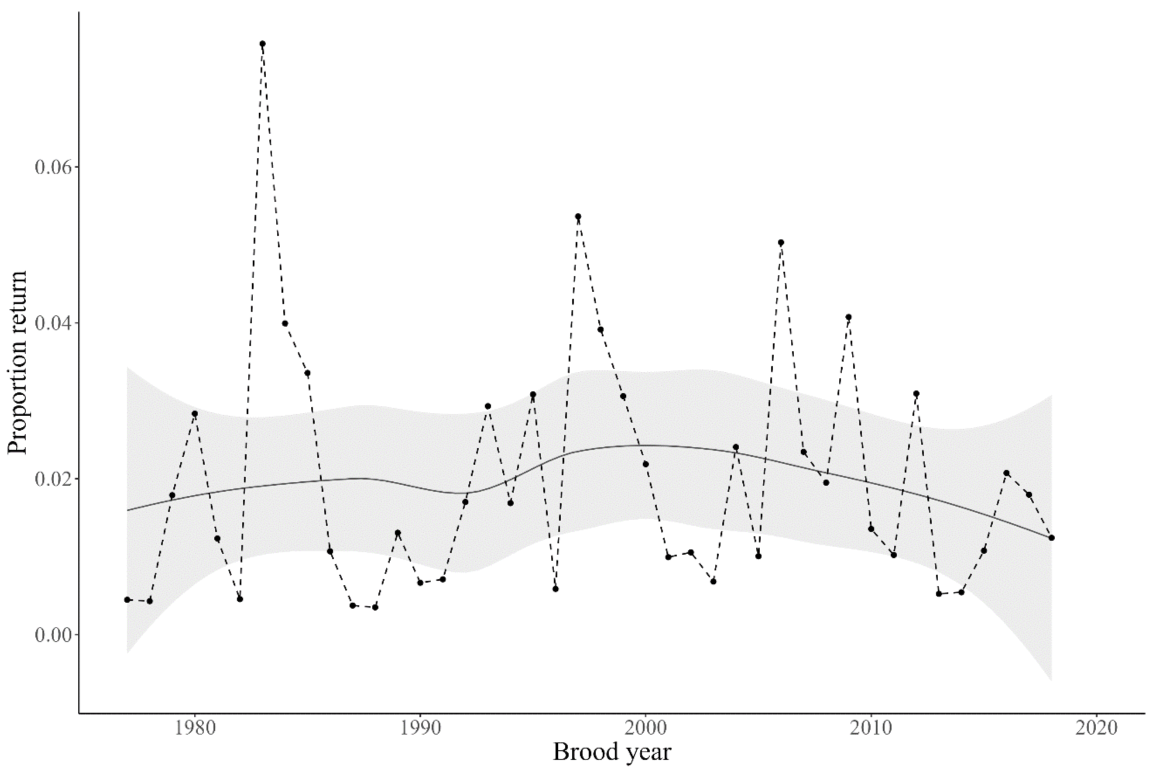


Synthesis Figure 2.11 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Salmon River fall Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

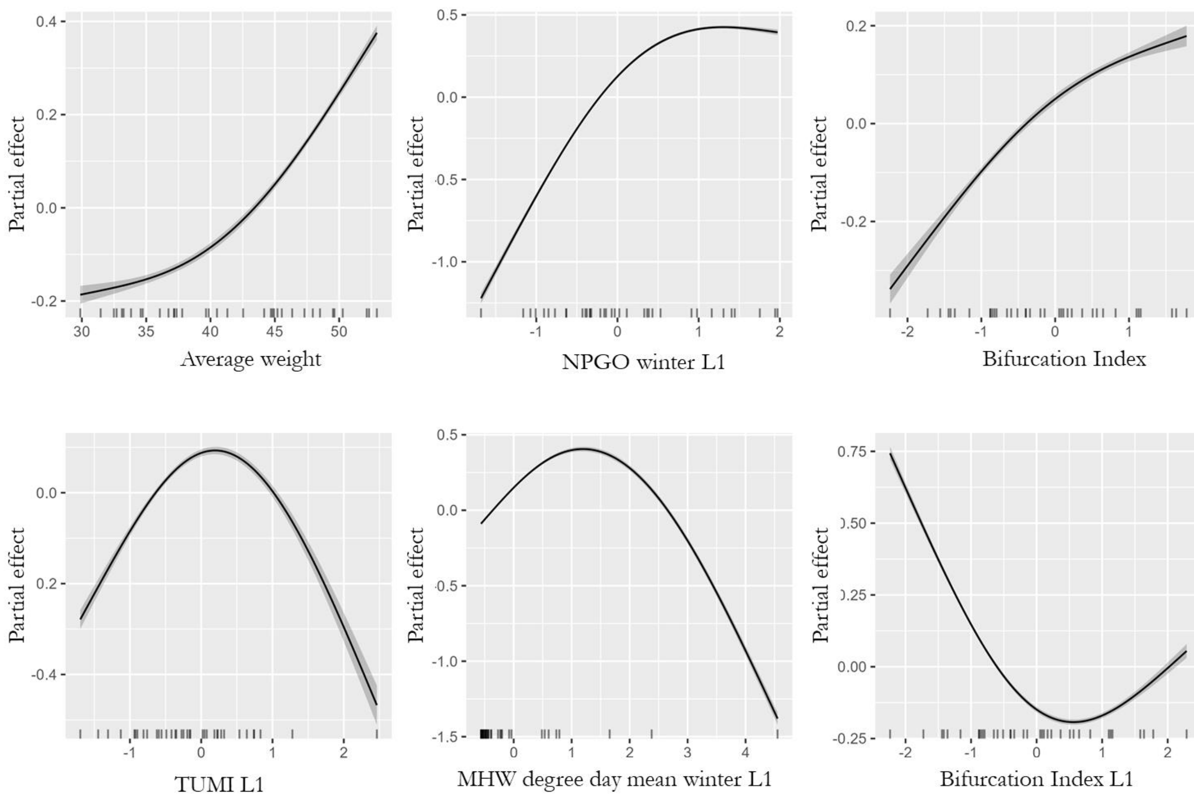
Elk River

Synthesis Table 2.2 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Elk River fall Chinook program.

Predictor	RMSE	AIC	Average absolute effect
Average weight	0.9722	2790.82	0.0001
NPGO winter L1	0.9754	8000.06	0.0098
Bifurcation Index	0.9795	1330.74	0.0026
TUMI L1	0.9866	4004.19	0.0028
MHW degree day winter L1	0.9874	2779.02	0.0073



Synthesis Figure 2.2 Estimated proportion of returning individuals, categorized by brood year, for the Elk River fall Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

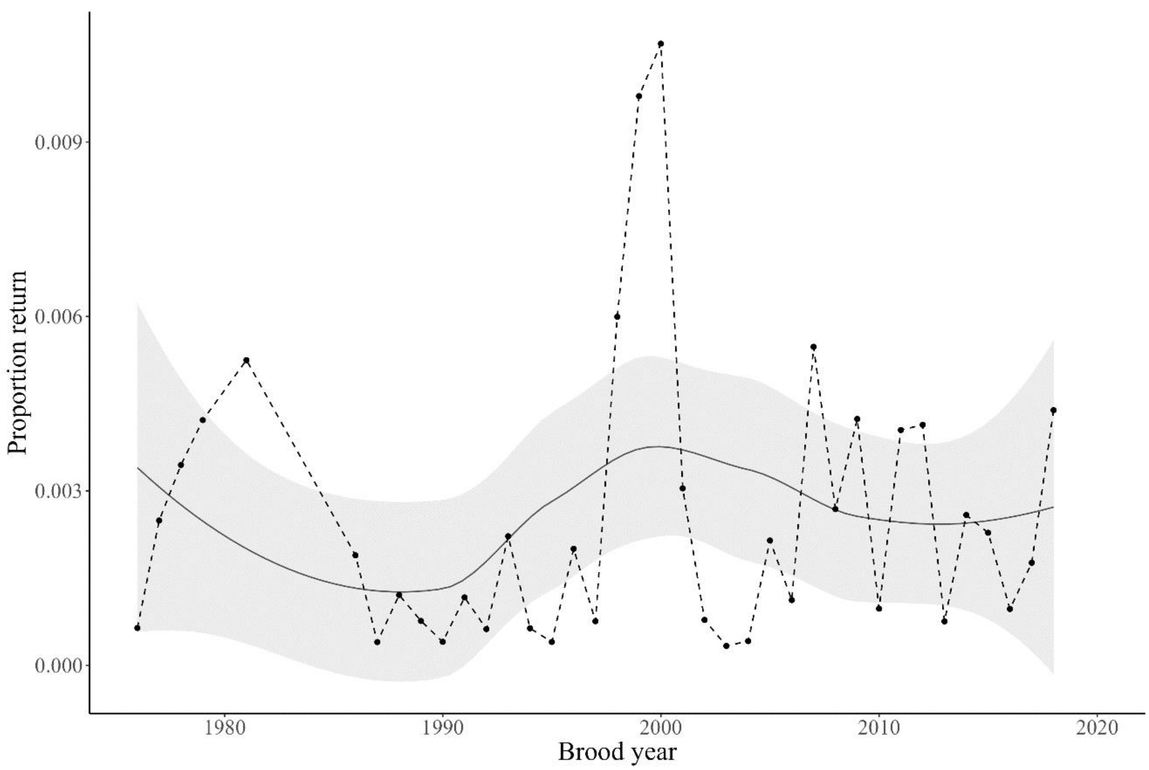


Synthesis Figure 2.21 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Elk River fall Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

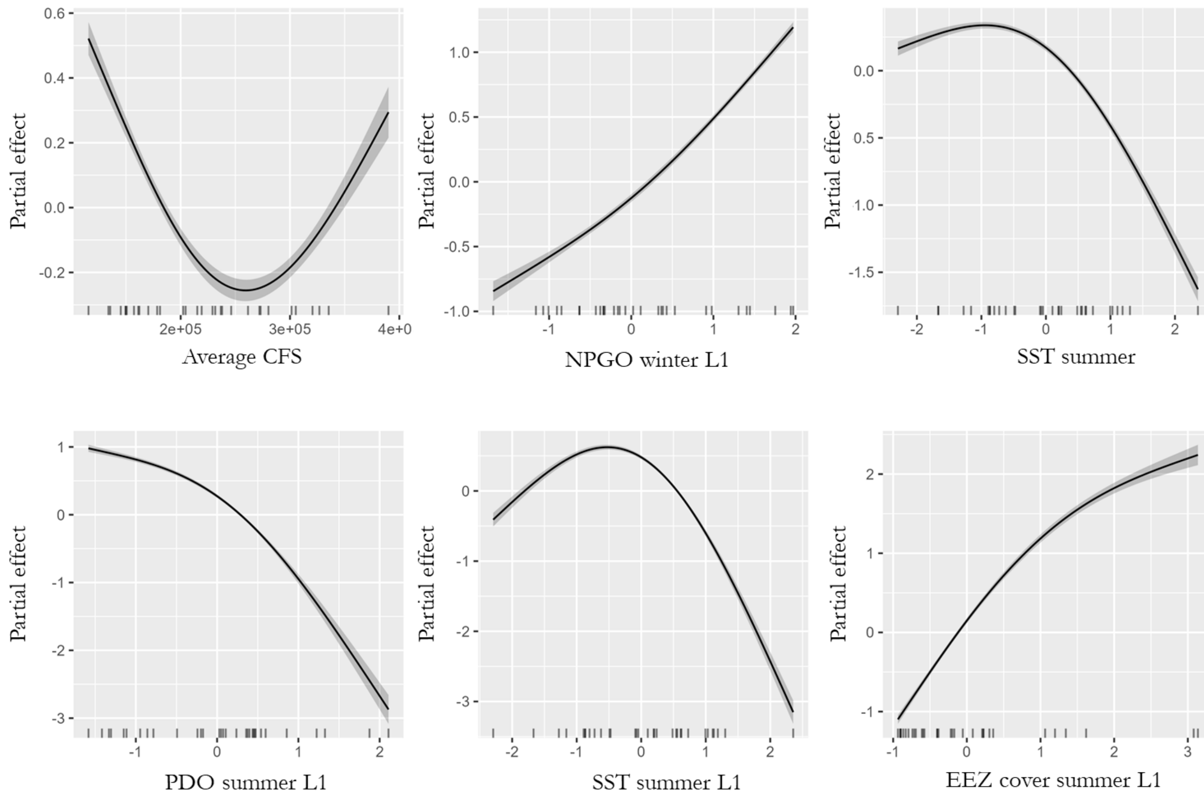
Big Creek

Synthesis Table 2.3 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Big Creek fall Chinook program.

Predictor	RMSE	AIC	Average absolute effect
NPGO winter L1	0.8497	3620.80	0.0019
SST summer	0.9257	2045.94	0.0010
PDO summer L1	0.9466	3071.71	0.0022
SST summer L1	0.9517	3515.14	0.0011
EEZ cover summer L1	0.9519	966.70	0.0040



Synthesis Figure 2.3 Estimated proportion of returning individuals, categorized by brood year, for the Big Creek fall Chinook program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.



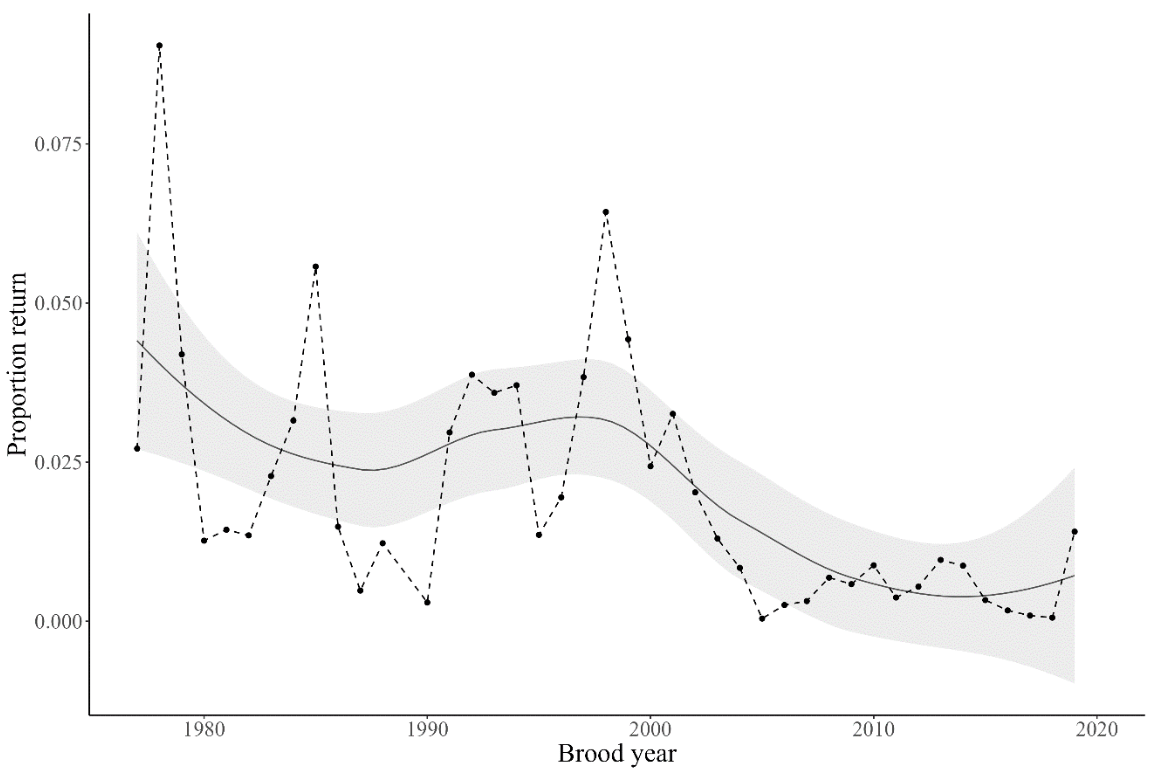
Synthesis Figure 2.31 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Big Creek fall Chinook program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

Coho Salmon

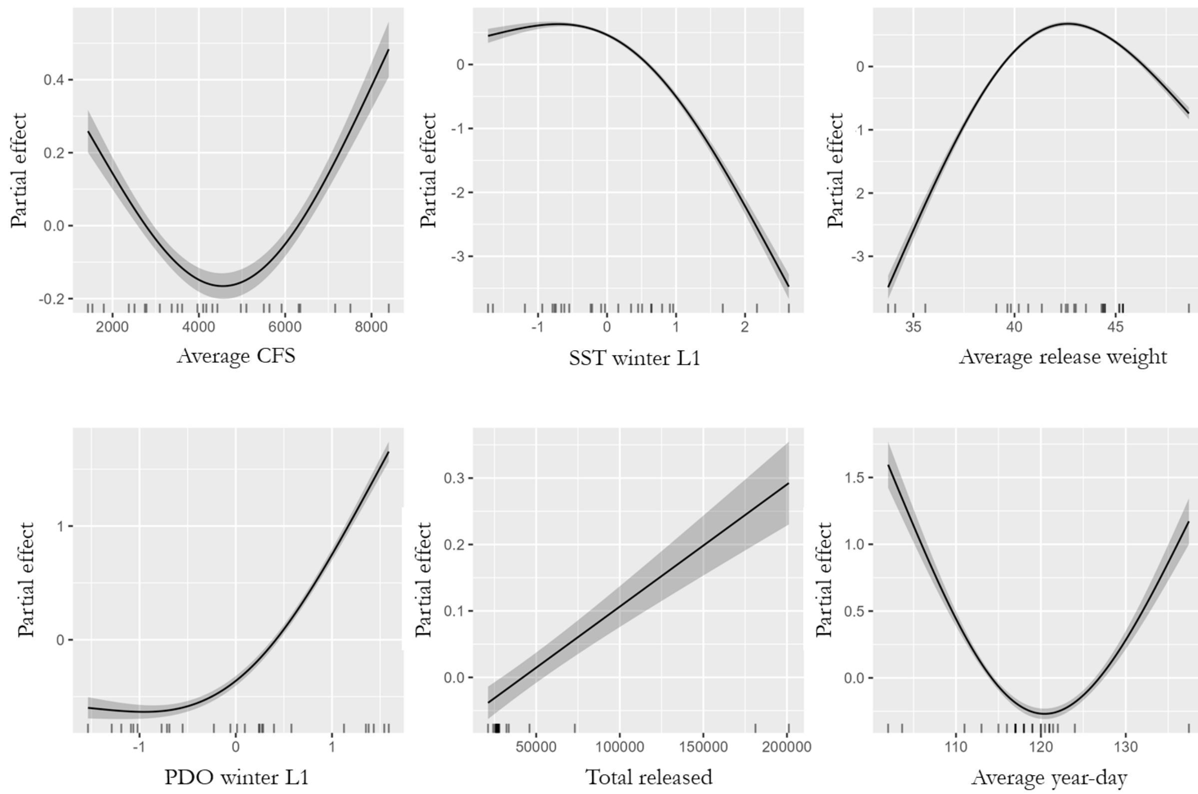
Rogue (Cole Rivers)

Synthesis Table 3.1 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Rogue (Cole Rivers) coho program.

Predictor	RMSE	AIC	Average absolute effect
SST winter L1	0.8726	1964.13	0.0062
Average weight	0.8730	2347.68	0.0000
PDO winter L1	0.8933	1861.14	0.0175
Total released	0.9002	2436.24	0.0000
Average year-day	0.9049	1666.55	0.0000



Synthesis Figure 3.1 Estimated proportion of returning individuals, categorized by brood year, for the Rogue (Cole Rivers) coho program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

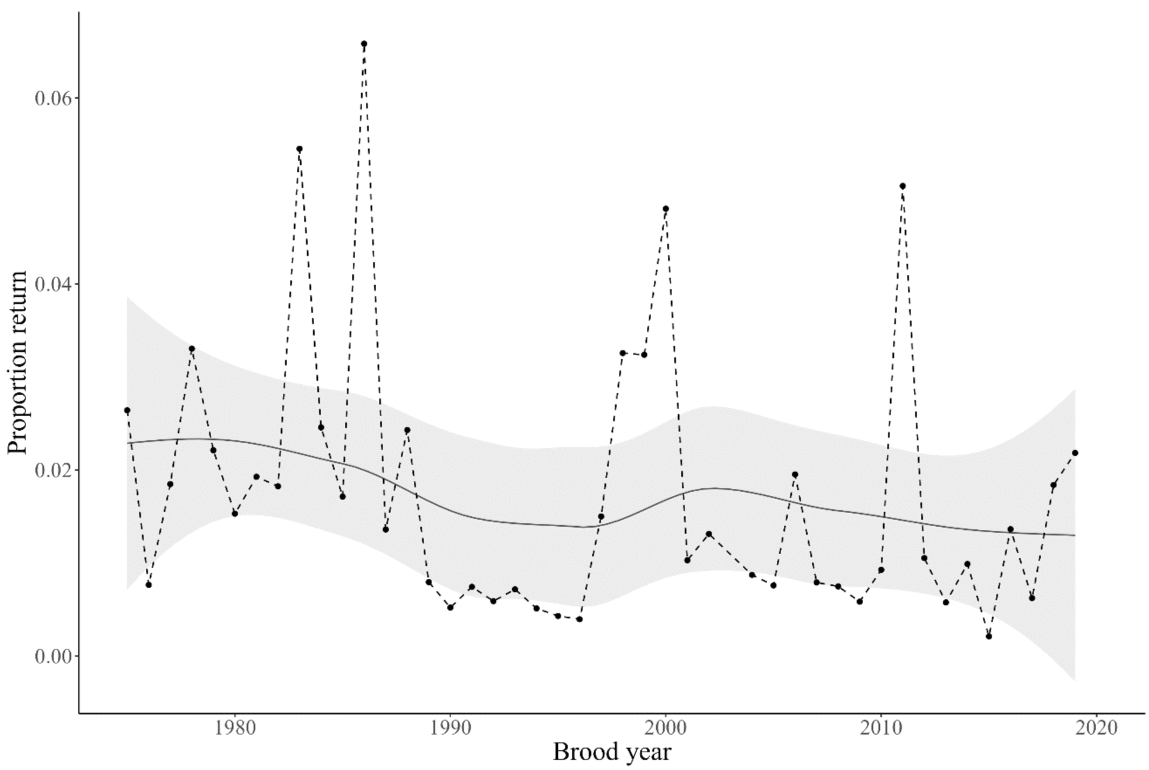


Synthesis Figure 3.11 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Rogue (Cole Rivers) coho program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

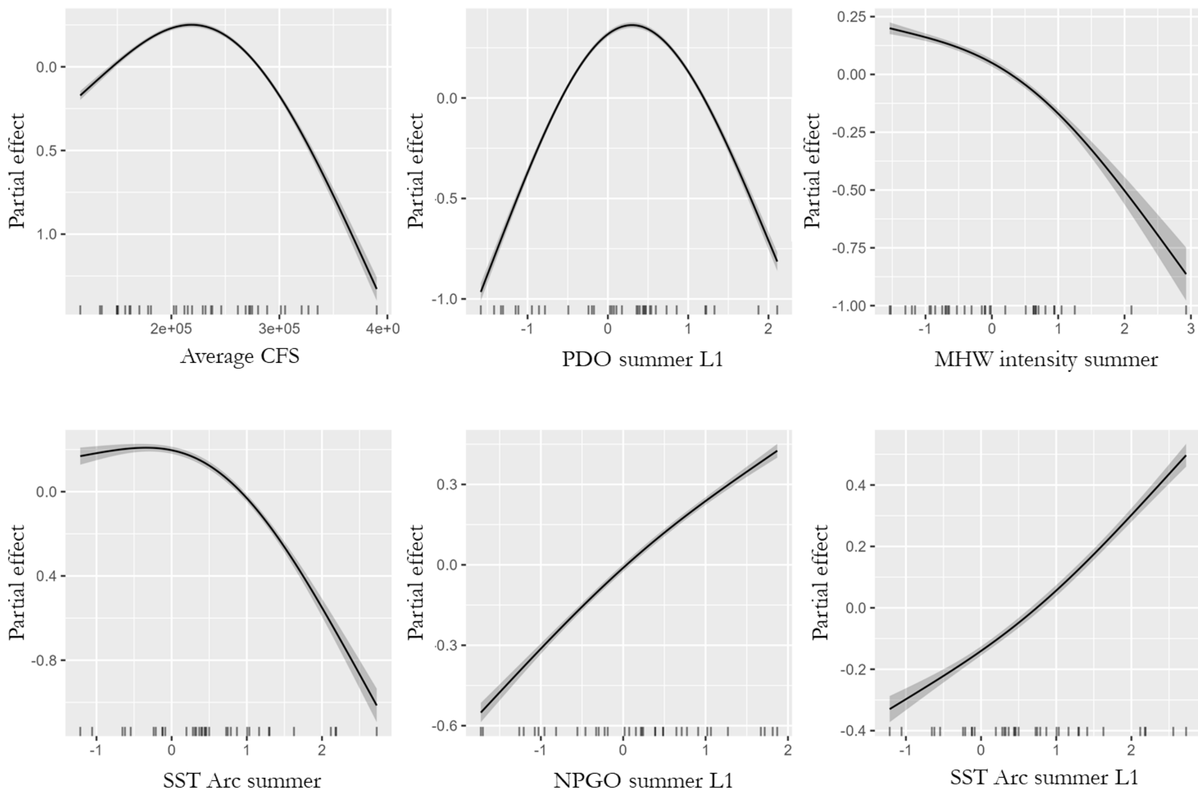
Big Creek

Synthesis Table 3.2 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Big Creek coho program.

Predictor	RMSE	AIC	Average absolute effect
PDO summer L1	0.8947	6092.34	0.0085
MHW intensity summer	0.9089	4652.10	0.0040
SST Arc summer	0.9426	3657.36	0.0027
NPGO summer L1	0.9446	2442.28	0.0068
SST Arc summer L1	0.9475	3347.86	0.0046



Synthesis Figure 3.2 Estimated proportion of returning individuals, categorized by brood year, for the Big Creek coho program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

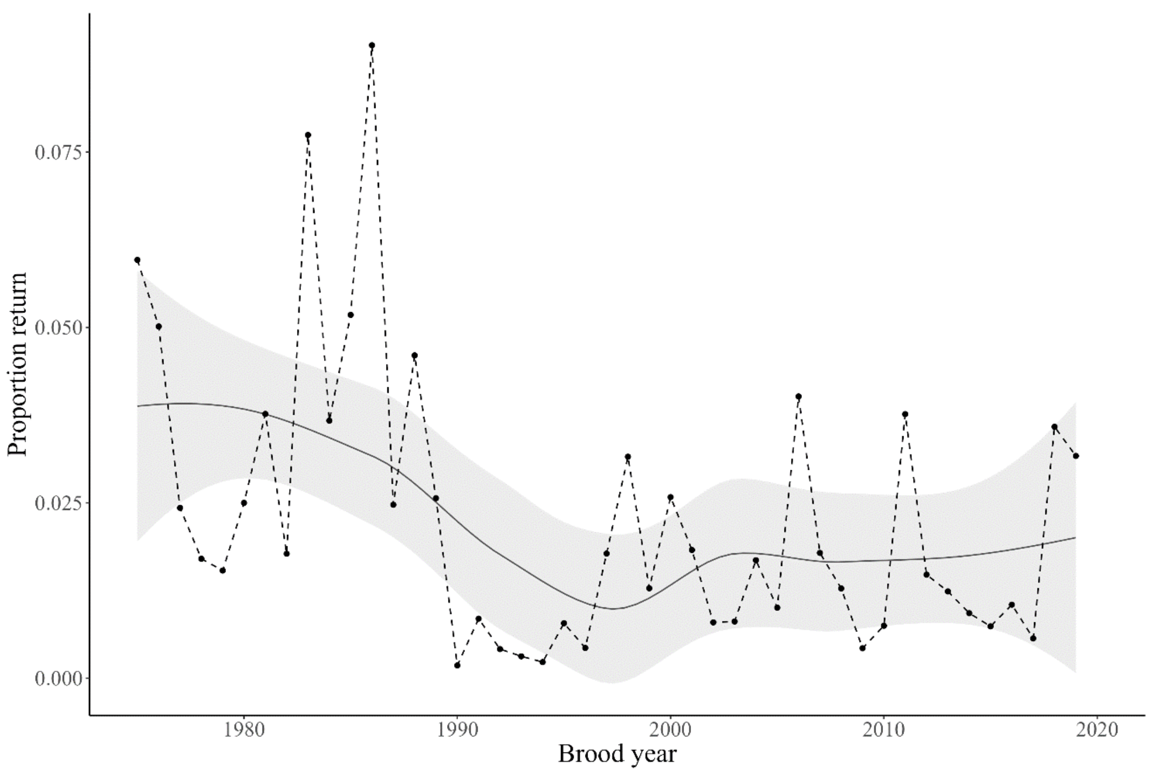


Synthesis Figure 3.21 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Big Creek coho program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

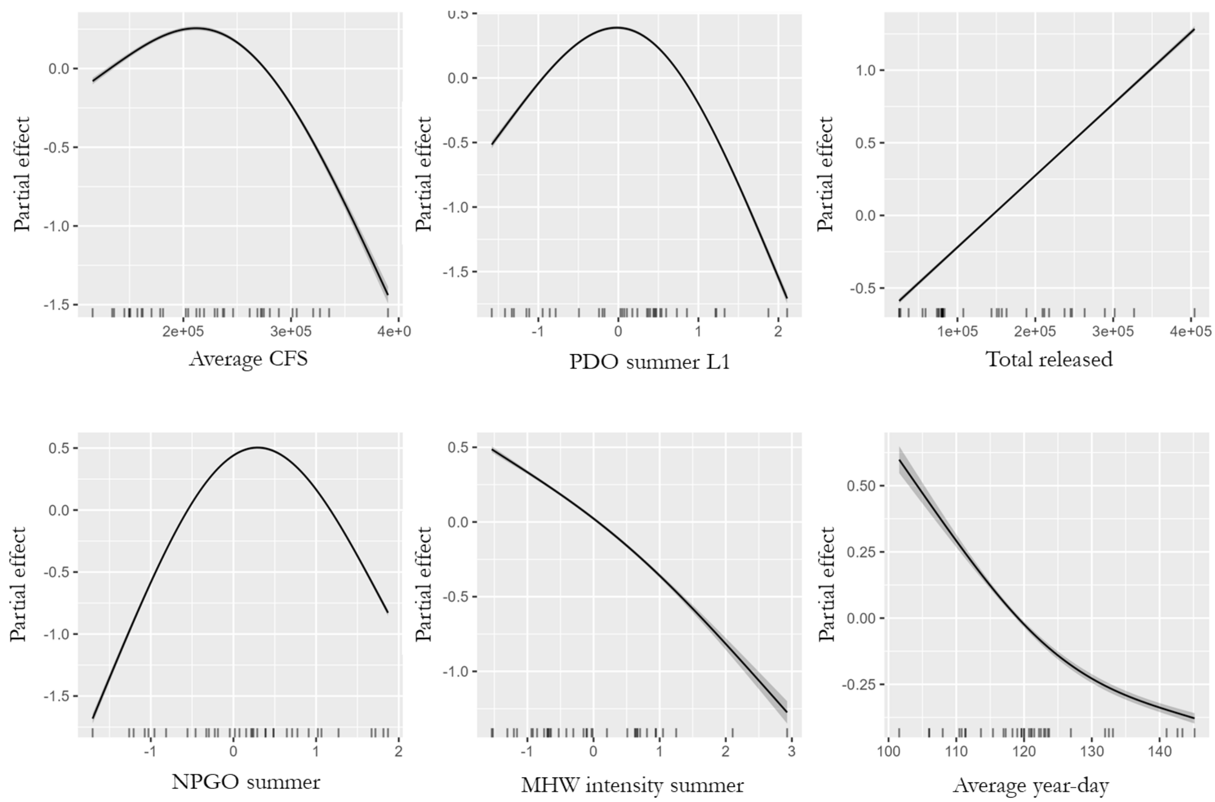
Sandy

Synthesis Table 3.3 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Sandy coho program.

Predictor	RMSE	AIC	Average absolute effect
PDO summer L1	0.8665	15979.08	0.0082
Total released	0.9103	16571.63	0.0000
NPGO summer	0.9318	11722.87	0.0091
MHW intensity summer	0.9385	13385.37	0.0070
Average year-day	0.9560	11175.91	0.0085



Synthesis Figure 3.3 Estimated proportion of returning individuals, categorized by brood year, for the Sandy coho program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.



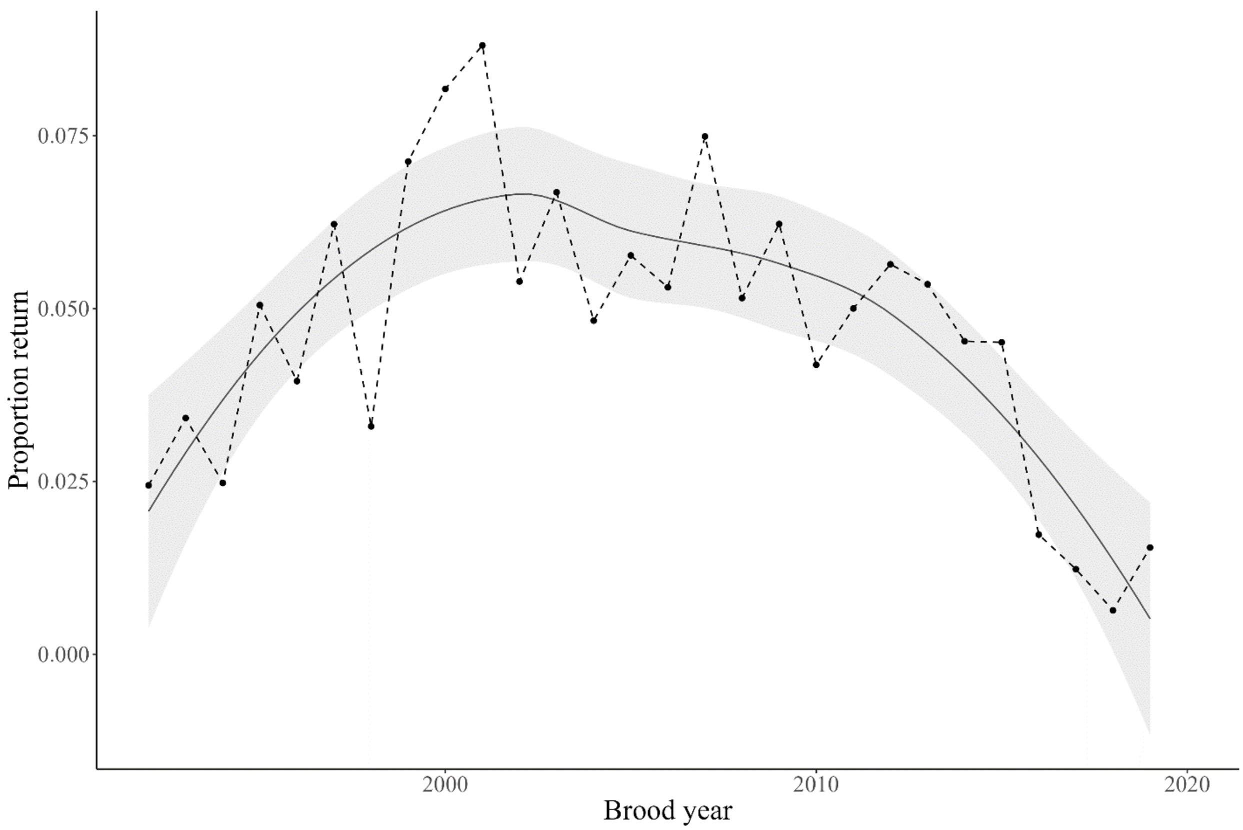
Synthesis Figure 3.31 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Sandy coho program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

Summer Steelhead

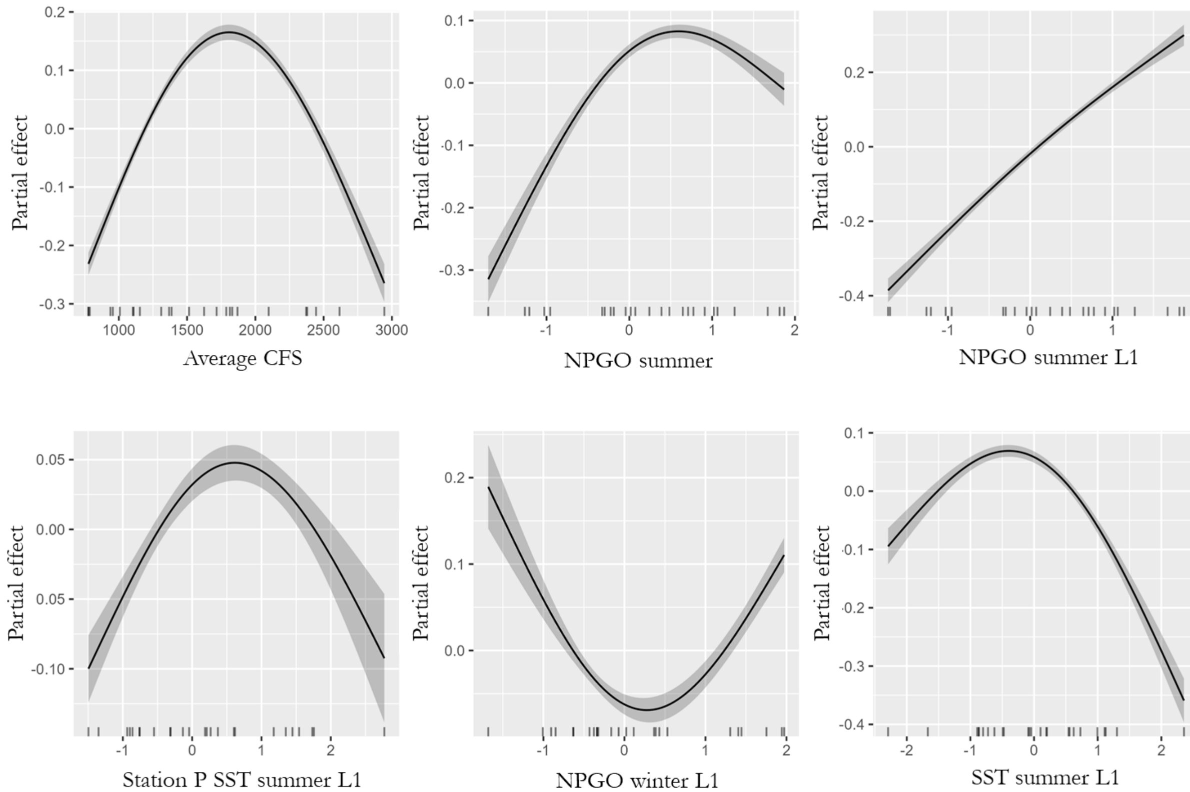
Siletz

Synthesis Table 4.1 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Siletz summer steelhead program.

Predictor	RMSE	AIC	Average absolute effect
NPGO summer	0.8168	2562.28	0.0053
NPGO summer L1	0.8431	2437.84	0.0107
Station P SST winter L1	0.8637	1539.79	0.0024
NPGO winter L1	0.9294	1502.37	0.0046
SST summer L1	0.9330	775.43	0.0035



Synthesis Figure 4.1 Estimated proportion of returning individuals, categorized by brood year, for the Siletz summer steelhead program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

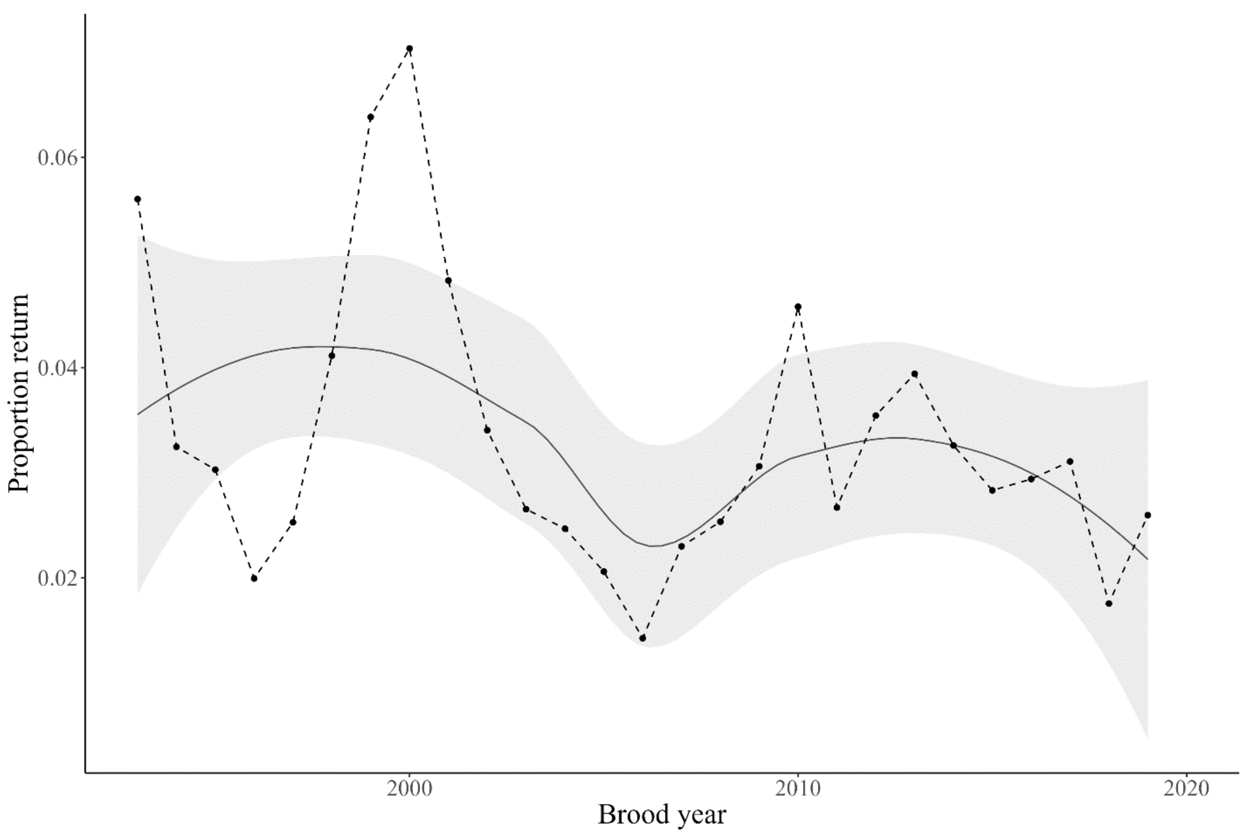


Synthesis Figure 4.11 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Siletz summer steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

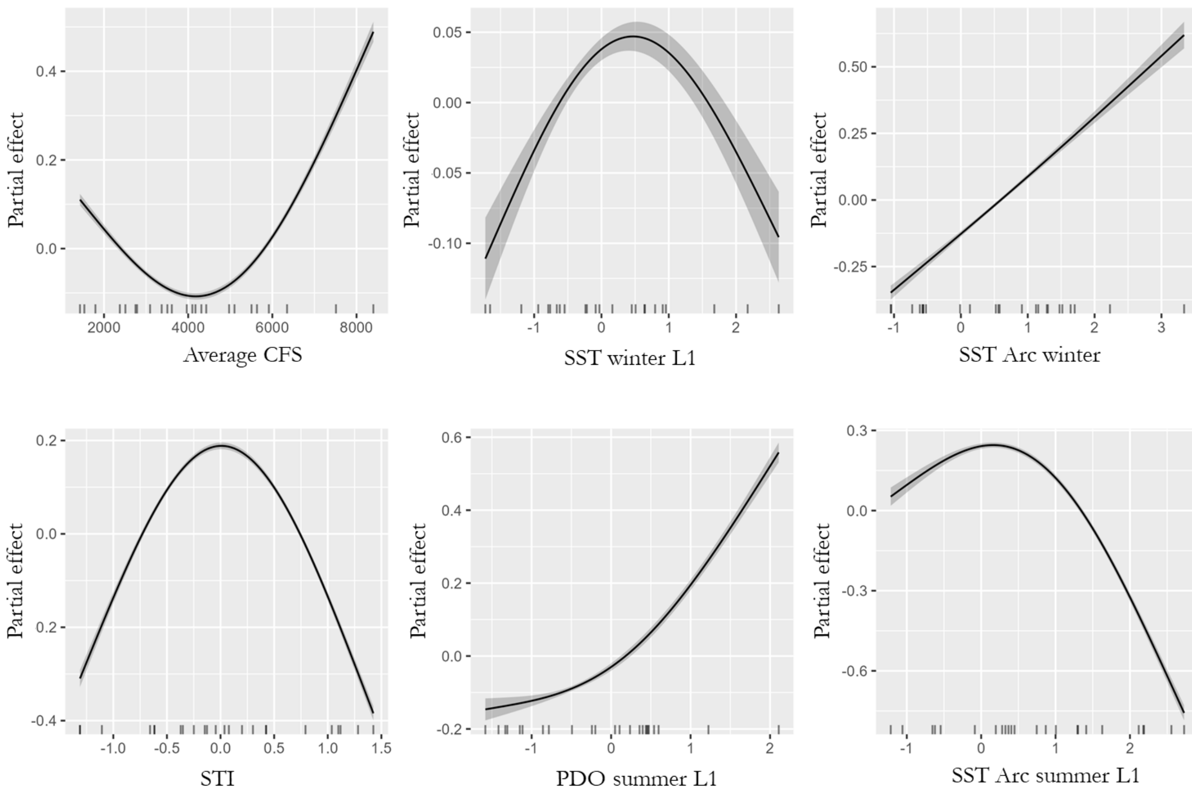
Rogue (Cole Rivers)

Synthesis Table 4.2 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Rogue (Cole Rivers) summer steelhead program.

Predictor	RMSE	AIC	Average absolute effect
SST winter L1	0.8820	3333.65	0.0014
SST Arc winter L1	0.8854	3218.78	0.0083
STI	0.9008	4328.75	0.0108
PDO summer L1	0.9102	4052.88	0.0066
SST Arc summer L1	0.9112	4673.86	0.0048



Synthesis Figure 4.2 Estimated proportion of returning individuals, categorized by brood year, for the Rogue (Cole Rivers) summer steelhead program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

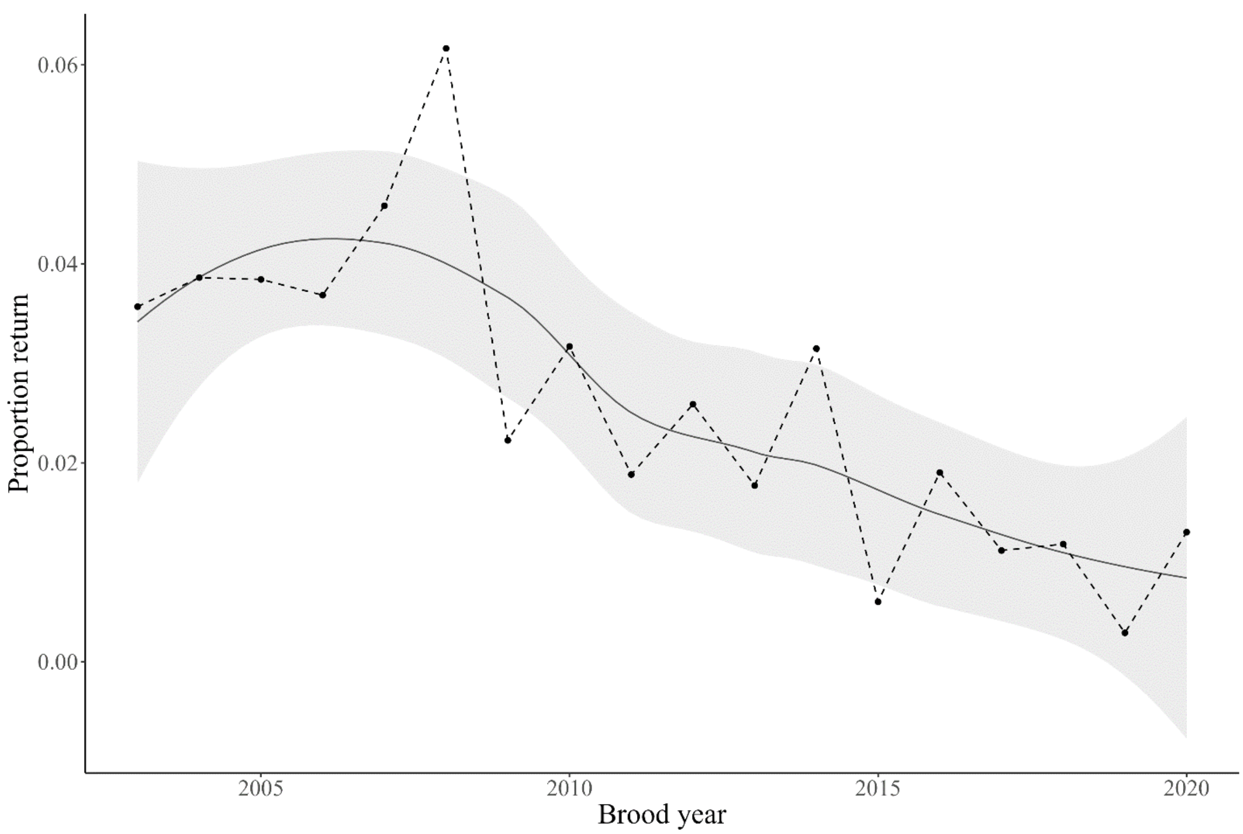


Synthesis Figure 4.21 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Rogue (Cole Rivers) summer steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

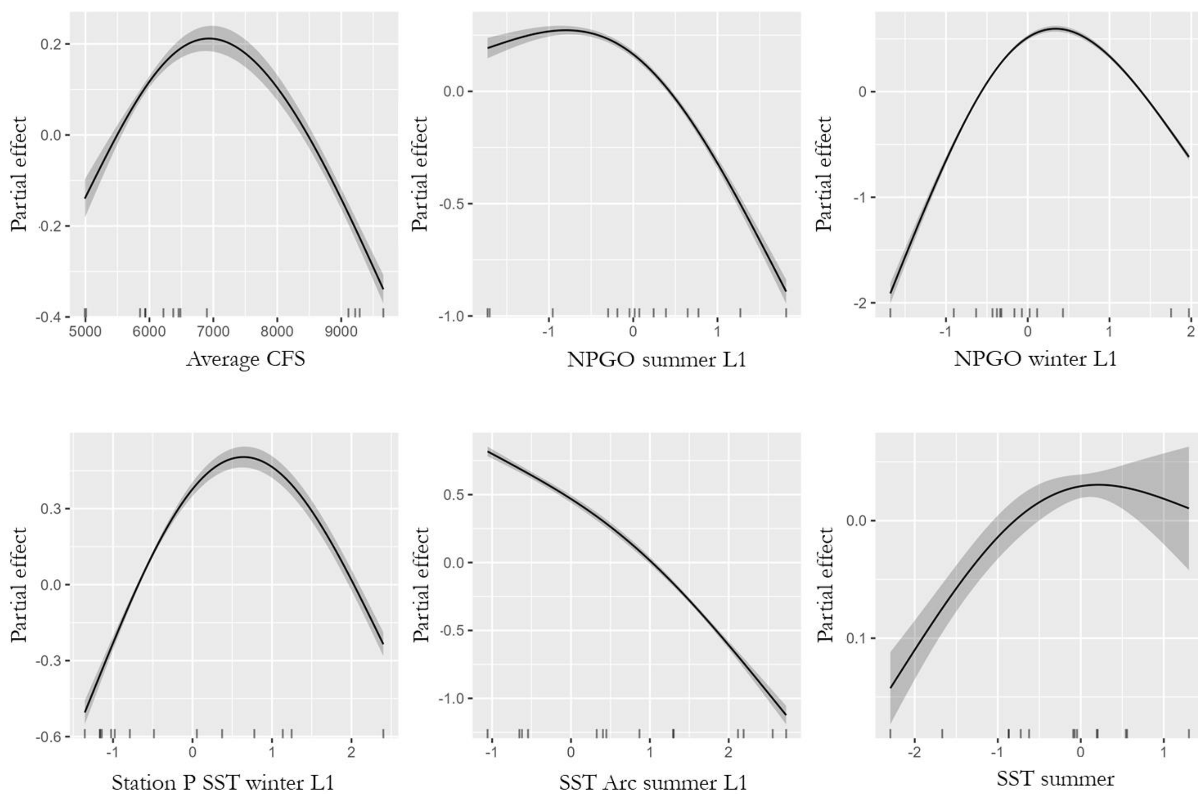
Deschutes (Round Butte)

Synthesis Table 4.3 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Deschutes (Round Butte) summer steelhead program.

Predictor	RMSE	AIC	Average absolute effect
NPGO summer L1	0.6350	5691.70	0.0310
NPGO winter L1	0.7176	3008.43	0.0562
Station P SST winter L1	0.7781	4796.54	0.0350
SST Arc summer L1	0.8132	5039.36	0.0458
SST summer	0.8216	3931.33	0.0032



Synthesis Figure 4.3 Estimated proportion of returning individuals, categorized by brood year, for the Deschutes (Round Butte) summer steelhead program Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

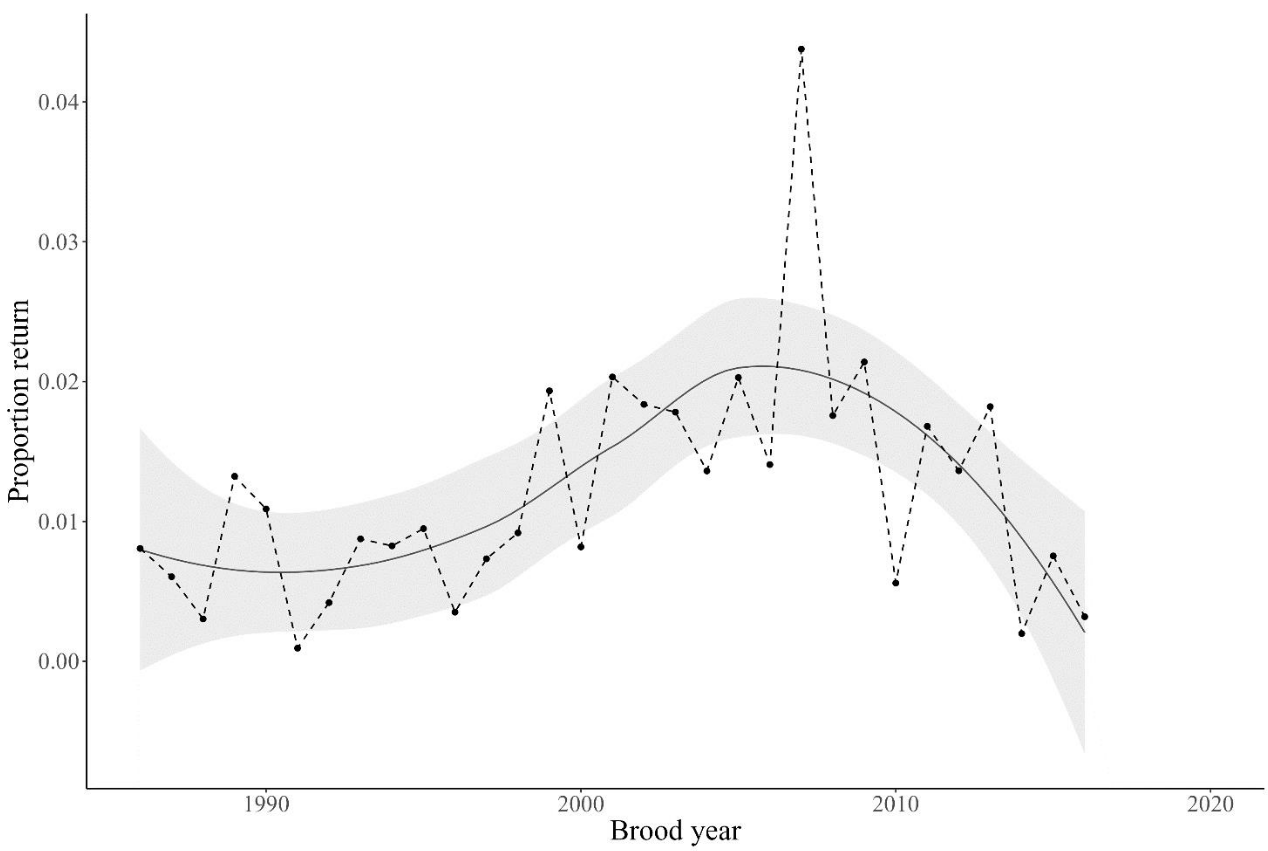


Synthesis Figure 4.31 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Deschutes (Round Butte) summer steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

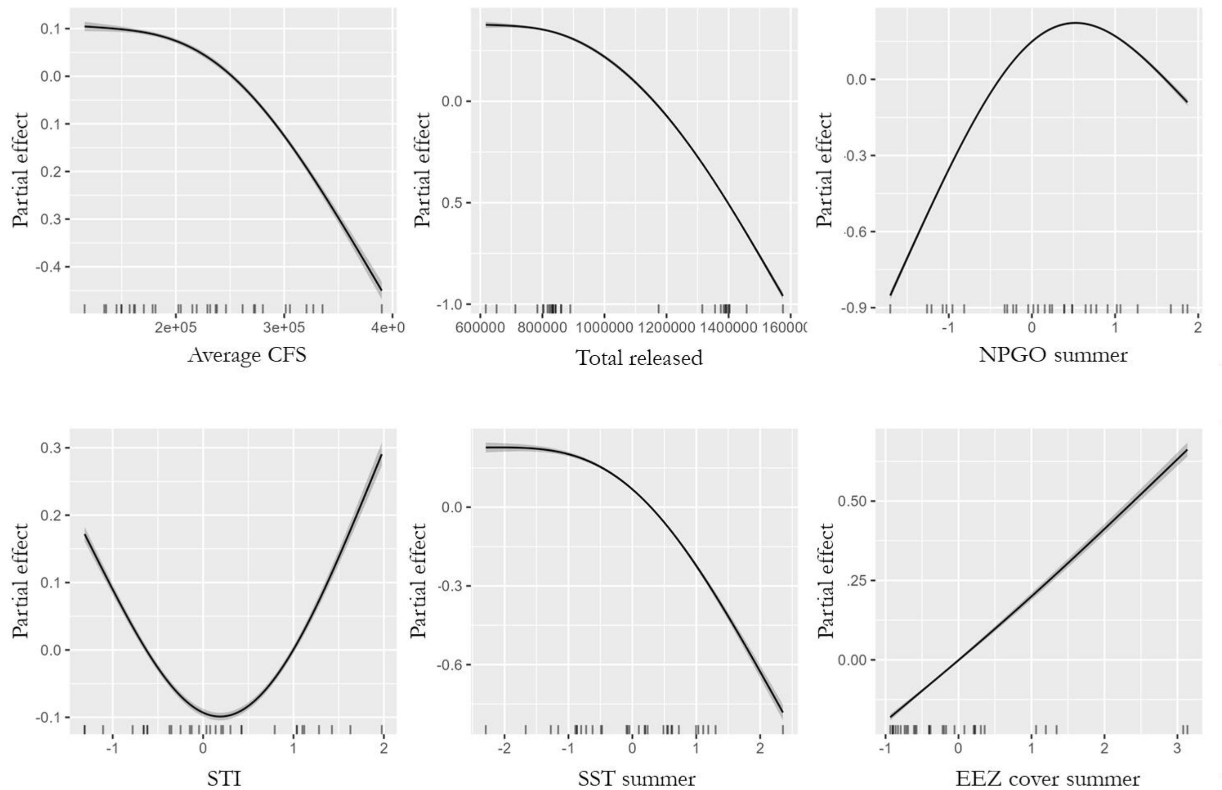
Wallowa

Synthesis Table 4.4 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Wallowa summer steelhead program.

Predictor	RMSE	AIC	Average absolute effect
Total released	0.8627	59462.34	0.0000
NPGO summer	0.8848	24201.21	0.0039
STI	0.9440	13661.10	0.0027
SST summer	0.9535	14913.02	0.0037
EEZ cover summer	0.9635	7256.62	0.0037



Synthesis Figure 4.4 Estimated proportion of returning individuals, categorized by brood year, for the Wallowa summer steelhead program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.



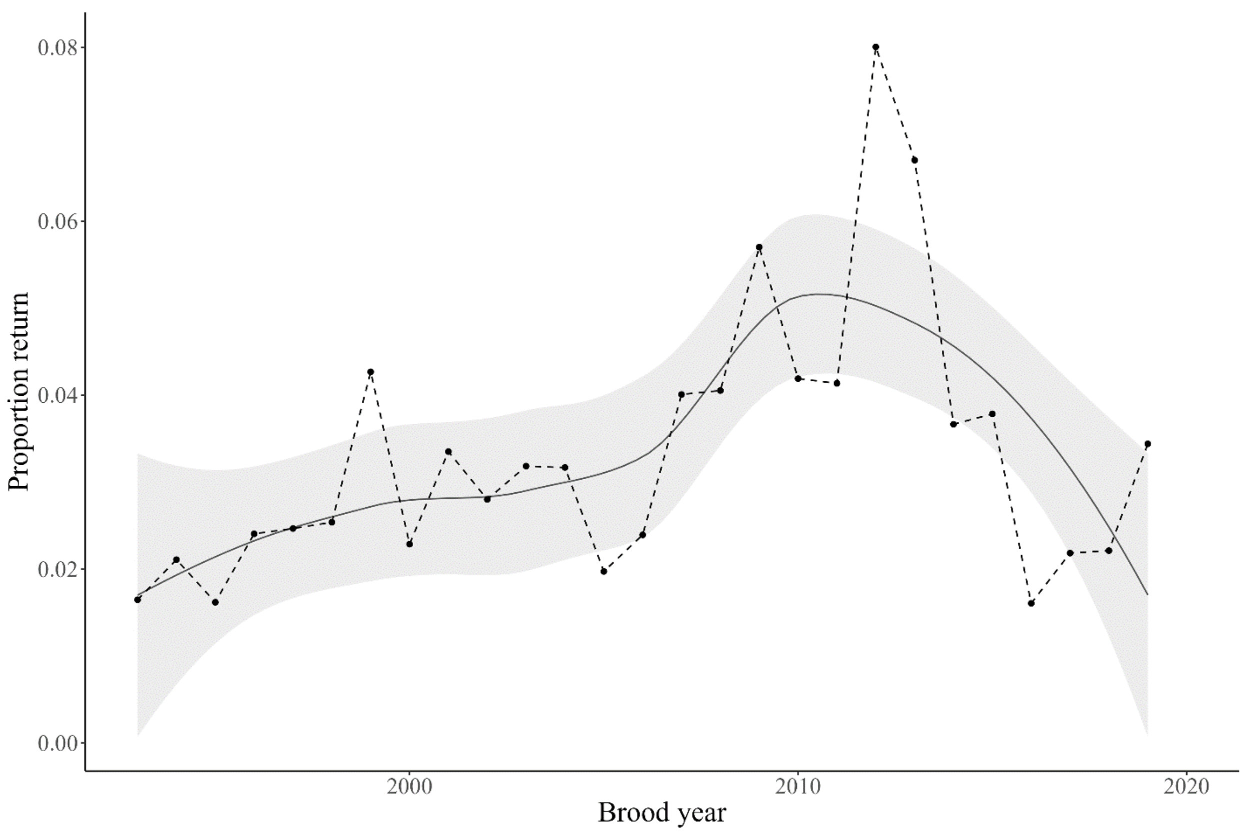
Synthesis Figure 4.41 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Wallowa summer steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

Winter Steelhead

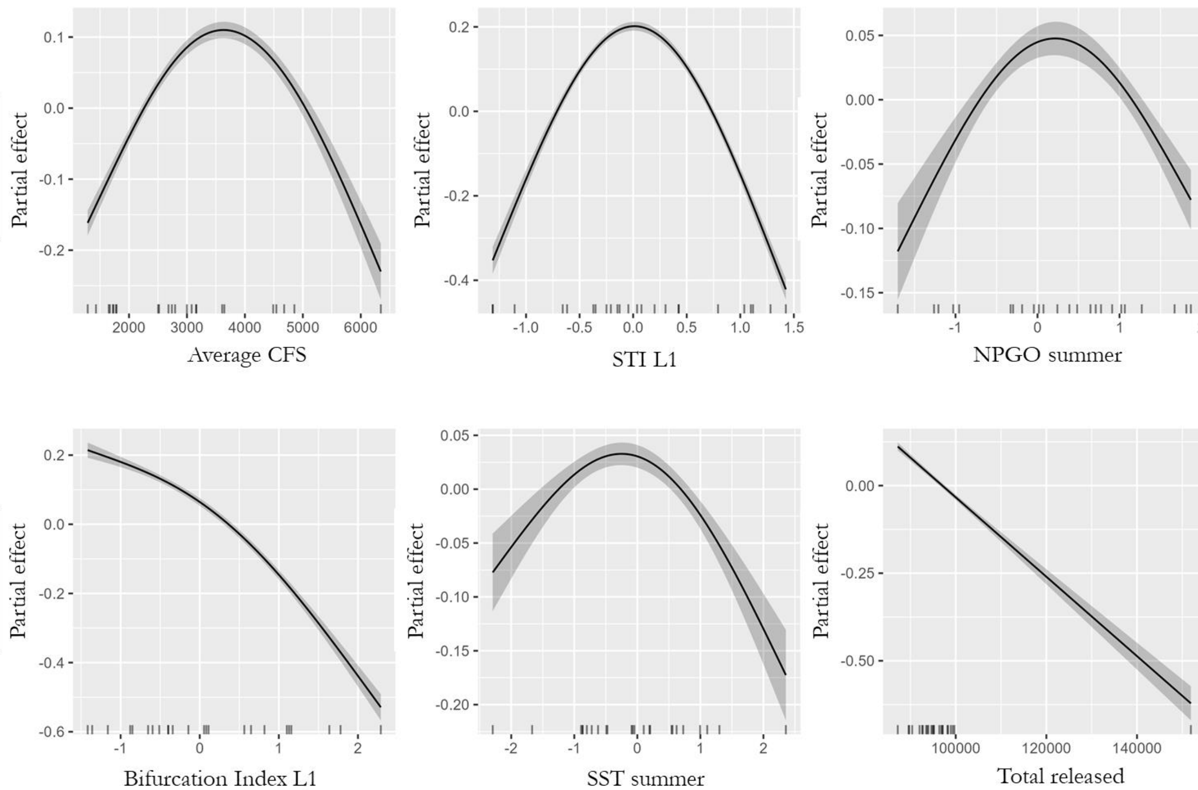
North Fork Nehalem

Synthesis Table 4.5 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the North Fork Nehalem winter steelhead program.

Predictor	RMSE	AIC	Average absolute effect
STI L1	0.8468	4193.16	0.0361
NPGO summer	0.8978	2879.46	0.0061
Bifurcation Index L1	0.9208	1936.86	0.0182
SST summer	0.9406	1089.50	0.0041
Total released	0.9467	1996.00	0.0000



Synthesis Figure 4.5 Estimated proportion of returning individuals, categorized by brood year, for the North Fork Nehalem winter steelhead program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.

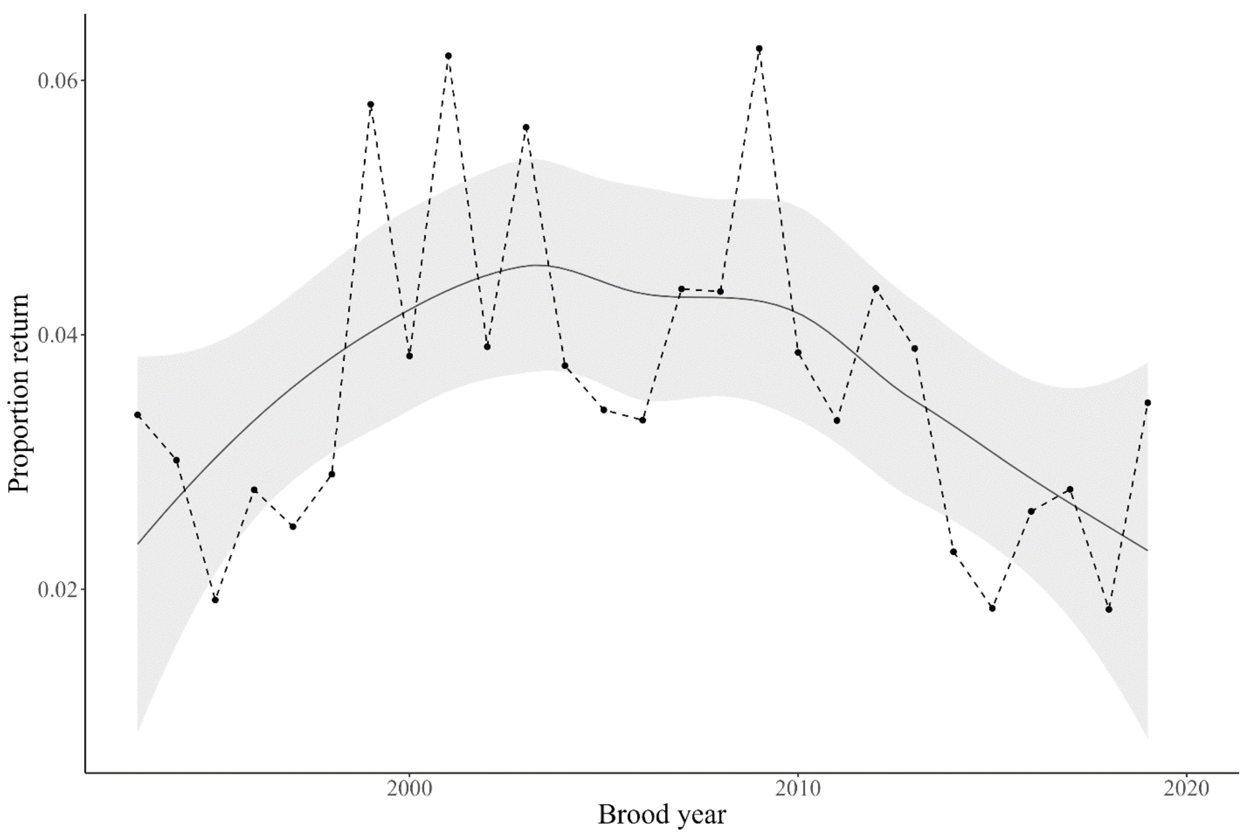


Synthesis Figure 4.51 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the North Fork Nehalem winter steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.

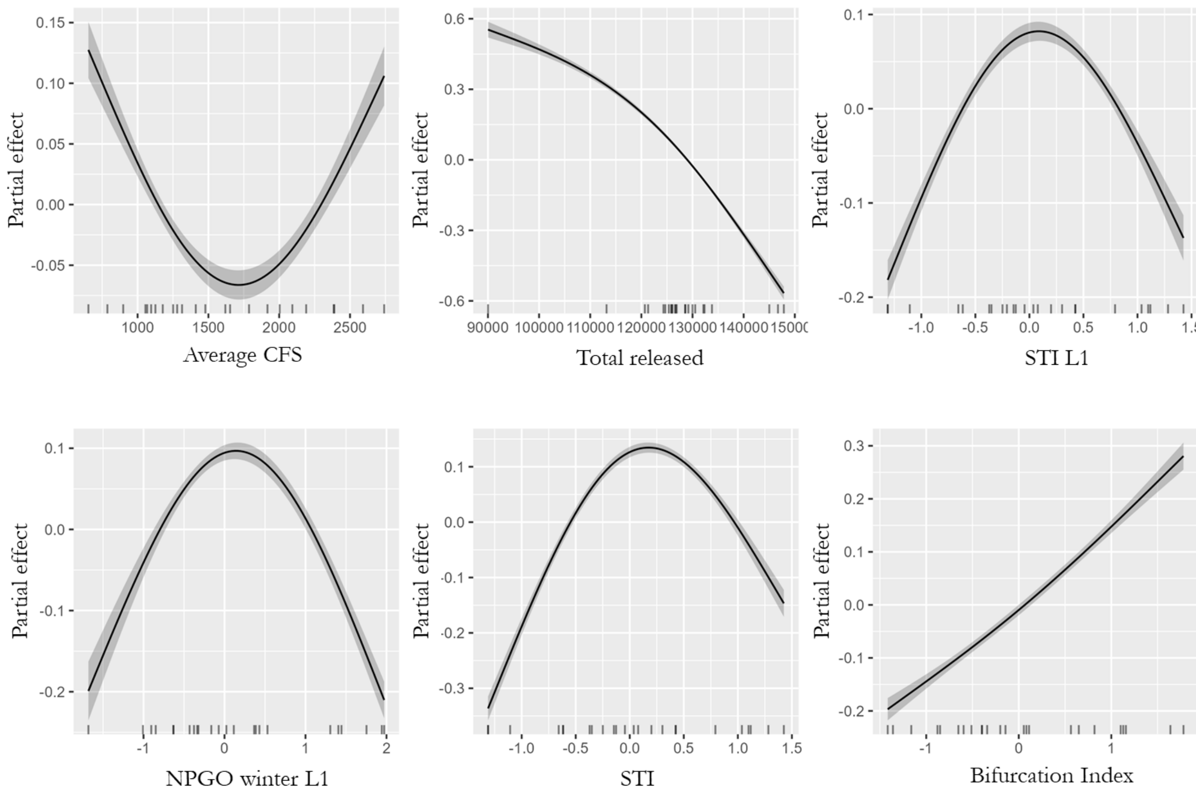
Alsea

Synthesis Table 4.6 Table of estimate Root Mean Squared Error (RMSE, lower is better), Akaike's Information Criterion (AIC, lower translates to more data support), and estimated average absolute effect sizes of standardized predictors (larger effects have a bigger impact on the response) for the Alsea winter steelhead program.

Predictor	RMSE	AIC	Average absolute effect
Total released	0.8159	3332.44	0.0000
STI L1	0.8444	3026.86	0.0170
NPGO winter L1	0.9067	2063.74	0.0127
STI	0.9197	1638.36	0.0251
Bifurcation Index	0.9239	1781.57	0.0180



Synthesis Figure 4.6 Estimated proportion of returning individuals, categorized by brood year, for the Alsea winter steelhead program. Points represent empirical means, the solid line represents a LOESS-smoothed fit to the mean proportions, and the grey ribbon represents a 95% confidence interval.



Synthesis Figure 4.61 Estimated partial effects of the top six predictors with the lowest (best) RMSE for the Alsea winter steelhead program. Solid lines show the estimated smooth effect (using splines) of each predictor, and the shaded ribbons indicate the 95% confidence intervals for the estimated effects.