Supplement to “A watershed-specific formula to predict salmon reproduction using functional flow metrics”

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Feb. 2025

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# 1 History of flow-ecology relationships

A river’s flow regime is often referred to as a “master variable” controlling geomorphic, chemical, and other conditions in its aquatic ecosystems, and organisms that have evolved to persist in specific flow regimes are commonly negatively affected by flow alteration (Bunn and Arthington 2002; Poff et al. 2010). Consequently, in recent decades a diverse body of research has sought to identify and quantify ecological responses to changes in flow.

Work on this topic spans multiple categories of ecological response, hydrologic predictor, and ultimate cause of hydrologic alteration. Two widely studied ecological response metric categories are, firstly, the stream health index, based on density and species richness of macroinvertebrates observed at designated sampling sites (e.g., Monk et al. 2006; Guareschi et al. 2014; Kevic et al. 2018; Mazor et al. 2018; Larsen et al. 2021; Peek et al. 2022), and secondly, fish diversity and community assemblage (e.g., McManamay et al. 2013; Peterson and Freeman 2016; Cartwright et al. 2017; Sinnathamby et al. 2018; Hain et al. 2018; Guedes et al. 2020; Yao et al. 2021). Ecological responses can also be based on the abundance of a single or a few species, often of fish (Stewart-Koster et al. 2011; Booth et al. 2014; DeWeber and Peterson 2020; Hale et al. 2023), as well as the extent of habitat types (Chowdhury and Driver 2007; Arriana Brand et al. 2011) and the presence of organisms including vegetation and plankton (Riis et al. 2008; Catford et al. 2014; Qian, Liu, and Chen 2016; Tesfaye et al. 2017; Saby et al. 2022). Hydrologic predictors range widely **insert IHA and ELOHA**, with a heavy emphasis on extreme (low or high) flow events and the duration of components of the flow regime (e.g., Ayllón et al. 2014; Lamouroux and Olivier 2015; McManamay and Frimpong 2015; Bower et al. 2022). Causes of the change in hydrology include the operation of dams, changes in human water use, climate change, and natural flow variability (e.g., Alomía Herrera and Carrera Burneo 2017; Gao, Xie, and Zou 2020; White et al. 2018; Daneshvar et al. 2017; Herbst et al. 2019).

Investigations of flow-ecology relationships can also be grouped by approach Brummer et al. (2016). In experimental flow studies the flow is directly manipulated with dam releases and biological responses are monitored (e.g., Konrad et al. 2011). In longitudinal studies, long-term ecological and hydrological records can be used to infer local or regional correlations (e.g., Mellado-Díaz et al. 2019). Finally, in space-for-time approaches, the hydrology of multiple river systems in a region is used to populate the distribution of different hydrologic behavior, and ecological monitoring is related to flow differences between streams (e.g., Monk et al. 2008; Riis et al. 2008; Catford et al. 2014; Bower et al. 2022). Space-for-time analyses require considerably fewer resources than experimental flows and longitudinal studies, and thus are more numerous (Brummer et al. 2016).

Bridging the gap between science and policy has been a persistent challenge in this field. In many cases a key research motivation is to support decision-making in a variety of contexts, including dam operation, river restoration, and regulations of water extraction and land use (Richter et al. 2006; Han et al. 2015; Sinnathamby et al. 2018; Bradley et al. 2017; Brummer et al. 2016). But historical approaches based on relationship-finding are several steps removed from the policy-making process (Webb et al. 2018). For example, the Ecological Limits of Hydrologic Alteration (ELOHA) framework or similar approaches can generate flow-ecology relationships or flow standards for particular rivers, but cannot translate specific management decisions into hydrologic or ecological outcomes (Richter et al. 2006; Cartwright et al. 2017).

An ideal framework for supporting decision-making would involve two key steps, firstly connecting land and water management actions to flow changes, and secondly connecting flow changes to ecological responses (Peterson and Freeman 2016; DeWeber and Peterson 2020; Acero Triana, Chu, and Stein 2021). Both steps can involve complex models and substantial uncertainty, often representing an interdisciplinary challenge. Threshold values for “sufficient” flows would be ideal for a management context (Rosenfeld 2017), but can be difficult to identify and in some cases may not exist (Lueders and McManamay 2023). Additionally, identifying natural flow regimes may be less immediately relevant to water resource management than an approach which can quantify ecological responses to “designer” or functional flows (which can often be controlled or influenced by dam releases) (Arthington, Bernardo, and Ilhéu 2014; Webb et al. 2018), with the caveat that the designer flows approach may risk overlooking ecological flow needs that are not currently monitored (Bower et al. 2022). Finally, stakeholders in at least one study requested flow-ecology relationships based on empirical monitoring, rather than more easily-simulated proxies like flow changes or thermal exposure (DeWeber and Peterson 2020).

The present study is a longitudinal “bottom-up” analysis, using empirical data and a case study, to identify flows most critical to support two specific species, and thus address the second of the two key links identified above. We use empirical data to develop a predictive model of a biological response to measurable (and simulatable) changes in flow metrics. We refer to this model as a “hydrologic benefit function” (i.e., intending to quantify the ecological services provided by flow) for a single species. This provides the critical link to evaluate fish outcomes resulting from future alternative watershed management practices which affect the hydrology of a stream ecosystem. A forthcoming companion study will investigate the other link, simulating flow changes from watershed management actions using an appropriate hydrologic model, then use hydrologic benefit functions to summarize the ecologic outcomes of a portfolio of water and land use scenarios.

# 2 Scott River watershed setting and water use

## 2.1 Geography, climate and hydrology

The Scott River drains a 2,109 km2 (814 square mile) watershed known as Scott Valley, flowing generally from south to north and joining the Klamath River after flowing through a steep canyon (Figure ??). The Scott is a major tributary to the Klamath, which drains an area spanning sections of Northern California and Southern Oregon (Figure ??, inset map). Scott Valley has a Mediterranean climate with distinctive seasons of cool, wet winters and warm, dry summers. This seasonality in water input creates highly seasonal flow in the Scott River and tributary streams, where the beginning of a water year coincides with low flow conditions that immediately precede the onset of winter precipitation (Figure 1).

In most dry-to-average water years, sections of the Scott River become seasonally dewatered (NCRWQCB 2005; Figure 5 in Tolley, Foglia, and Harter 2019). This occurs when the elevation of the water table drops below the bottom of the river channel, as streams and groundwater are highly interconnected in the Scott River watershed. Tributary streams, particularly along their alluvial fan apeces, and the upper Scott River are sources of recharge to the aquifer (Mack 1958; Harter and Hines 2008). Groundwater discharge sustains streamflow in low-lying areas, especially during the dry season of August through October or November (Tolley, Foglia, and Harter 2019). For consistency with regulatory and management programs in this region, this document uses units of cubic feet per second (cfs) when reporting hydrologic fluxes.

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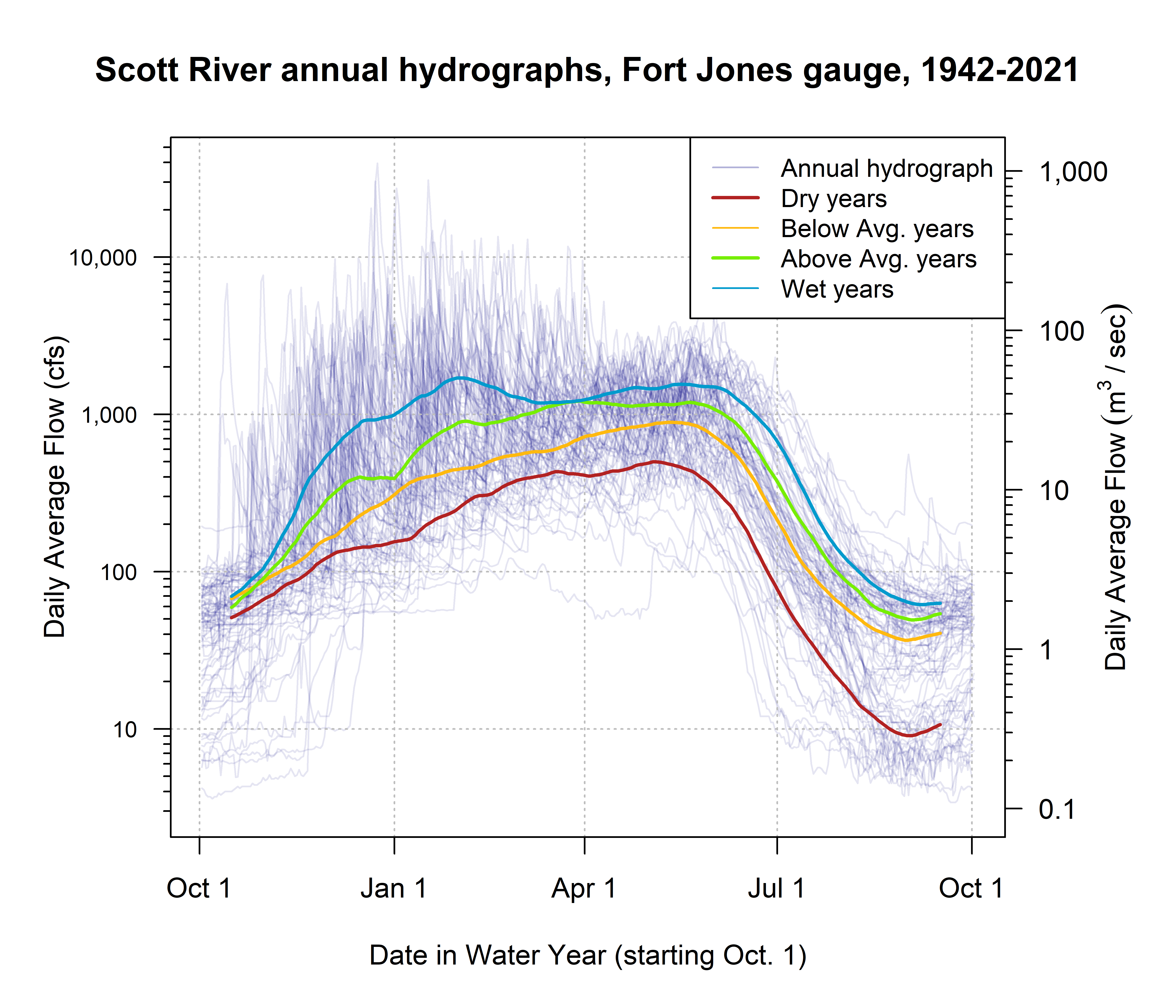


Figure 1: Each translucent line traces one annual hydrograph measured at the Fort Jones gauge, and the darker lines illustrate the 30-day smoothed median daily flow in Dry, Below Average, Above Average, and Wet water year types, for water years 1942-2023. The water year type is defined by quartiles of the distribution of total annual flow.

## 2.2 Water uses and management objectives

Water in Scott Valley is used for agricultural, domestic, and municipal supply. It also facilitates recreation and provides Native American cultural services, among other designated beneficial uses (NCRWQCB 2006). Because the watershed is undammed, managers and water users influence Scott River flow primarily via diversion of surface waters and pumping of groundwater. Consequently, the most powerful tool available to manage Scott River water flow is regulation of land use and thus water demand (Siskiyou County 2021).

Historically, local regulation of land use has focused on maintaining the rural and agricultural character of Scott Valley (Scott Valley Area Plan Committee 1980). Regulating land use to improve ecological outcomes would entail significant economic, political and social risks, because much of the economic activity in this area is related to agriculture. The primary crops grown in Scott Valley are pasture for cattle feed and alfalfa (Siskiyou County 2021). In addition to local economic impact, Scott River conditions influence fish population dynamics both within the watershed and in the broader Klamath system. The health of the Klamath salmon run has implications for commercial fishing, recreational activities, and cultural practices of Native American tribes in the region, including the Quartz Valley Indian Community and the Karuk and Yurok Tribes (Mansfield et al. 2012).

Recent management activity has included the leasing of surface water rights from landowners to enhance summer flows (e.g., SRWT 2018), the prioritization of stream reaches for habitat restoration (SRWC 2018), several pilot projects to construct and assess the impact of beaver dam analogs (BDAs) on aquatic habitat and fish populations (Yokel 2018), a coordinated rescue effort to relocate juvenile salmon that were cut off from outmigrating by disconnected river reaches (CDFW 2015), and the development of long-term groundwater management plan by Siskiyou County and local stakeholders (Siskiyou County 2021).

# 3 Species of concern - coho and Chinook salmon

### 3.0.1 Life cycle and status of coho salmon (*Oncorhynchus kisutch*)

Returning adult coho spawn in natal streams between November and January (Knechtle and Giudice 2020), and juvenile coho spend approximately one full year in freshwater streams before migrating to the ocean as smolts (Moyle 2002; McMahon 1983). In the Scott River system these natal streams are the tributaries along the margins of the valley floor (SRCD 2004).

In previous studies, the strongest predictor of juvenile coho abundance in a stream system was spatial habitat (Bradford, Taylor, and Allan 1997; Nickelson et al. 1992; Bustard and Narver 1975), although adequate food and cover were also important (McMahon 1983). The primary mechanism for spatial constraints on abundance appears to be that juvenile coho become more territorial as they grow (McMahon 1983).

Some coho salmon return to spawn at age 2 as grilse, but the majority (e.g., 92.4% in 2020) return after more than one year in the ocean, giving the Scott coho salmon run its characteristic 3-year cohort return interval (Knechtle and Giudice 2020).

Coho salmon in the Scott Valley are listed as threatened under the federal and California Endangered Species Acts (ESAs). They belong to the Southern Oregon / Northern California Coast (SONCC) Evolutionarily Significant Unit (ESU), which was listed as threatened under the federal and state ESAs in 1997 and 2005, respectively. State-wide, coho populations have declined more than 90% since the 1940s (Brown, Moyle, and Yoshiyama 1994).

### 3.0.2 Life cycle and status of Chinook salmon (*Onchorhynchus tsawytscha*)

Chinook salmon in the Scott Valley are a candidate for listing under the federal ESA, and are not listed under the California ESA. They belong to the Southern Oregon / Northern California Coast (SONCC) Evolutionarily Significant Unit (ESU). Typically, adult Chinook salmon return to spawn in Scott Valley streams in the fall months September-December when flows are sufficient for salmon passage (Knechtle and Giudice 2020; Magranet 2015, 2017). Chinook in this watershed hatch in the spring and migrate to the ocean in their first year of life (Agrawal et al. 2005). Chinook spend the majority of their life in the ocean, and return to their natal streams shortly before spawning (Groot and Margolis 1991). However, substantial variability exists within this broader structure: Chinook salmon exhibit variation in multiple life stages, including time of seaward migration, age of maturity, and timing of return to natal stream (Groot and Margolis 1991; Bourret, Caudill, and Keefer 2016).

As recently as 2013, the SONCC Chinook population was stable and becoming more complex (Wainwright et al. 2013). However, in monitoring from 2015-2020, the number of returning adults (the escapement) was 65% below historical average, and the change in the Scott River Chinook population has been more rapid than the decline in the overall Klamath Basin Chinook run (California Department of Fish and Wildlife 2021). Ocean conditions may have contributed to a broad decline in Chinook populations from Alaska to California (Welch, Porter, and Rechisky 2021). Some studies have found that the leading cause of declining Chinook populations are ocean conditions, including including temperature, upwelling currents and food resources (Hunt, Mulligan, and Komori 1999), while others have identified hatchery practices as the primary cause (Quiñones et al. 2014).

# 4 Functional Flows Background

Table 1: Explanation of functional flows used in this analysis (Patterson et al. 2020; Baruch et al. 2024). Each type of metric, for each threshold value (e.g., 100 cfs or 50th flow percentile), produces one value per water year.

| Abbrev. | Full Name | Thresholds | Description |
| --- | --- | --- | --- |
| DS\_Dur\_WS | Dry Season Duration | -- | Dry-season baseflow duration (# of days from start of dry season to start of wet season) |
| DS\_Tim | Dry Season Onset Timing | -- | Dry-season baseflow start timing (water year day of dry season) |
| DS\_Mag | Dry Season Flow Magnitude | 50th and 90th flow percentile | Percentile of daily flow within dry season. |
| FA\_Dur | Fall Pulse Duration | -- | Duration (# of days) of the fall pulse event |
| FA\_Tim | Fall Pulse Timing | -- | Start date of fall pulse event in water year days |
| FA\_Mag | Fall Pulse Magnitude | -- | Peak magnitude of fall pulse event (maximum daily peak flow during event) (cfs) in relevant lifestage. |
| FA\_Dif\_num | Fall Pulse Magnitude (modified) |  | Difference between peak fall pulse discharge and dry season median discharge (Baruch et al. 2024). |
| Wet\_BFL\_Dur | Wet Season Baseflow Duration | -- | Wet-season baseflow duration (# of days from start of wet-season to start of spring season) |
| Wet\_BFL\_Mag | Wet Season Baseflow Magnitude | 50th and 10th percentile | The magnitude of the median rate of baseflow (i.e., non-storm flow) during the wet season. |
| Wet\_Tim | Wet Season Onset Timing | -- | Start date of wet-season in water year days |
| Peak\_Dur | Duration of high-flow events | 2, 5, and 10-year return interval | Number of days exceeding the 2, 5 and 10 year recurrence intervals of annual peak flow (50%, 20%, and 10% exceedance values). |
| Peak\_Fre | Frequency of high-flow events | 2, 5, and 10-year return interval | Number of times that flow crosses over the threshold values for the 2-, 5- and 10-year flow (50%, 20%, and 10% exceedance values). |
| Peak\_Tim | Timing of first high-flow event in a water year | 2, 5, and 10-year return interval | Timing of first exceedance of threshold value for the 2-, 5- and 10-year flow (50%, 20% and 10% exceedance values), in water year days |
| Peak | Magnitude of high-flow events | 2, 5, and 10-year return interval | Single value for each threshold corresponding to the 2-, 5- and 10- year flow exceedance values, in cfs |
| SP\_ROC | Spring Recession Rate of Change | -- | Spring flow recession rate (median daily rate of change over decreasing periods during the recession) |
| SP\_ROC\_Max | Maximum Spring Recession Rate of Change |  | Maximum daily rate of change over decreasing periods during the recession |
| SP\_Dur | Duration of Spring Recession |  | Period elapsed from the start date of the spring recession until the start date of the following dry season. |
| SP\_Mag | Magnitude of Spring Recession |  | Flow magnitude on the start date of the spring recession (the "peak" of the snowmelt pulse). |
| SP\_Tim | Spring Onset Timing | -- | Start date of spring flow recession in water year days |
| Mean\_Ann\_Flow | Mean Annual Flow | -- | Mean daily flow rate over a full water year. |
| WY\_Cat | Water Year Category | -- | Category of water year (Dry, Moderate, Wet) |

## [1] FALSE



Figure 2: Figure 2 from Yarnell et al., 2020. Illustration of five functional flow categories identified for a mixed rain-snowmelt runoff river in California.

# 5 Hydrologic Metrics Designed for This Study

Table 2: Explanation of custom hydrologic metrics designed for this study, which are less complex than functional flows in that they do not rely on signal processing techniques. Each type of metric, for each threshold value (e.g., 120 cfs), produces one value per water year. Metric names used in predictive modeling also include abbreviations for salmon life periods (Table 3 below); e.g., f1\_recon\_120, referring to the timing of flow exceeding 120 cfs in a ohort's first fall season.

| Abbrev. | Full Name | Thresholds | Description |
| --- | --- | --- | --- |
| recon | River Reconnection Day (for a given life stage and threshold) | 20, 120 | The day, usually in the fall, on which the Scott River gains a certain degree of connectivity. Defined as the first day on which FJ Gauge flow rises above a designated threshold (e.g., 20 cfs) (units of days after Aug. 31). Assigned to a salmon lifestage using a season identifier such as f1 (first fall, experienced by a cohort's spawning parents). Example: f1\_recon\_20 |
| discon | River Disconnection Day (for a given life stage and threshold) | 20, 120 | The day, usually in the spring or early summer, on which the Scott River loses a certain degree of connectivity. Defined as the first day on which FJ Gauge flow drops below a designated threshold (e.g., 120 cfs) (units of days after Aug. 31). Assigned to a salmon lifestage using a season identifier such as s2 (second spring, experienced as outmigrating smolt). Example: s2\_discon\_120 |
| num\_days\_gt\_90\_pctile | Number of days of high-flow events | 90th flow percentile | Number of days in a water year in which the FJ daily average flow exceeded the 90th percentile flowrate in the full FJ Gauge record. |

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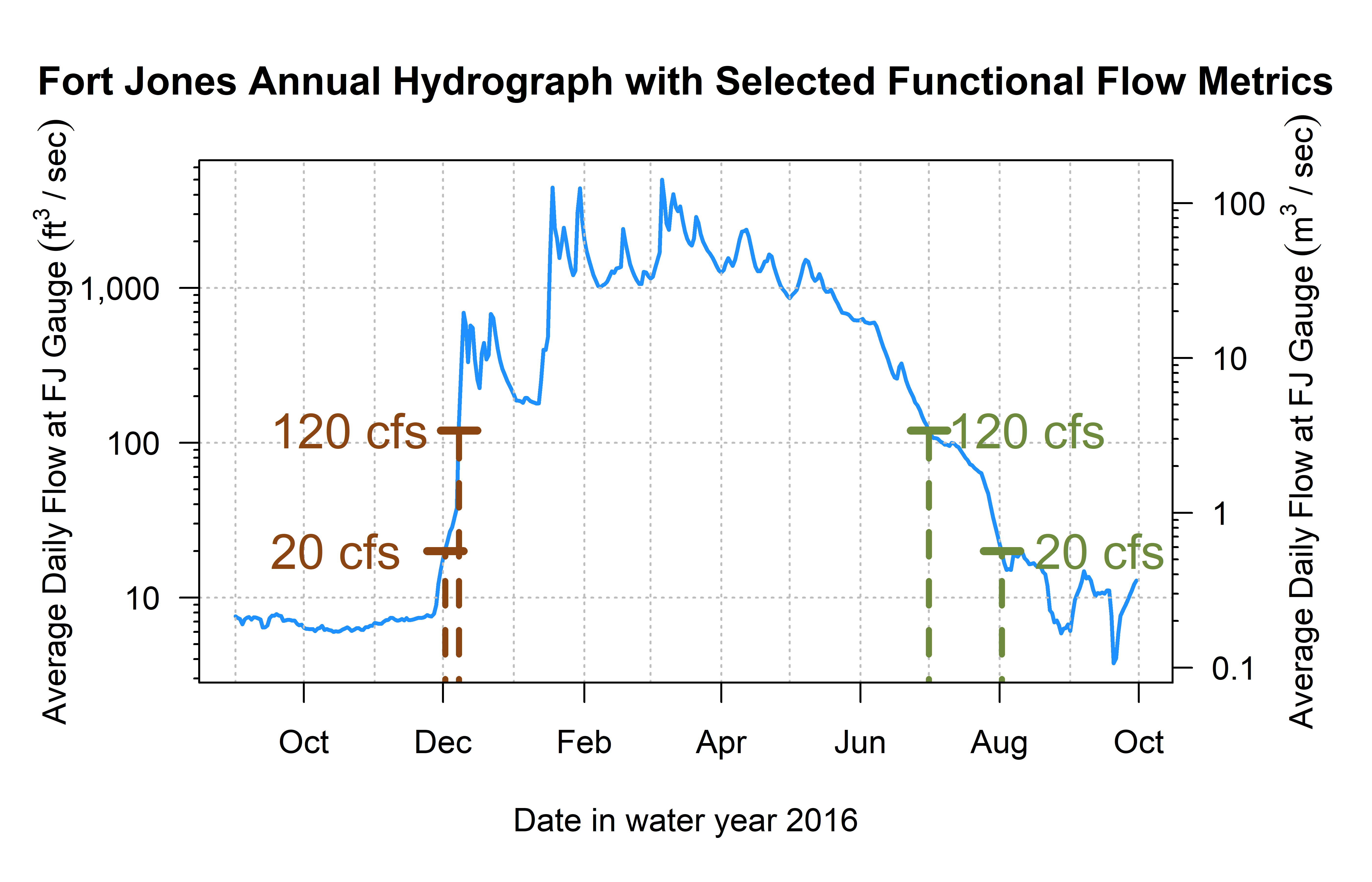


Figure 3: Reconnection and disconnection dates are highlighted for one water year. Two example thresholds, 20 and 120 cfs (0.57 and 3.4 cms, respectively) are highlighted, which correspond to distinct river connectivity (and salmon habitat access) conditions in the Scott River watershed as observed at the Fort Jones gauge (see Results for more detail on selection of flow thresholds).

# 6 Screening Predictors for Collinearity

Table 3: Groups of collinear predictors (absolute value of R greater than 0.7), interpretation of their hydrologic significance, and the predictor selected from each group to reduce collinearity.

| Group of Collinear Predictors | Hydrologic Significance (Coho Life Stage) | Predictor Selected from Group |
| --- | --- | --- |
| wy1\_Mean\_Ann\_Flow, s1\_discon\_20, s1\_discon\_40, s1\_discon\_120, f2\_recon\_20, f2\_recon\_40, w1\_Wet\_BFL\_Mag\_10, w1\_Wet\_BFL\_Mag\_50, s1\_SP\_Dur, s1\_SP\_Mag, wy1\_WY\_Cat, d2\_DS\_Tim, d2\_DS\_Mag\_50, d2\_DS\_Mag\_90, w1\_num\_days\_gt\_90\_pctile | How wet was the wet season? (year 1, as eggs and fry) | w1\_Wet\_BFL\_Mag\_50 |
| wy2\_Mean\_Ann\_Flow, s2\_discon\_120, w2\_Wet\_BFL\_Mag\_10, w2\_Wet\_BFL\_Mag\_50, s2\_SP\_Dur, s2\_SP\_Mag, wy2\_WY\_Cat, w2\_num\_days\_gt\_90\_pctile | How wet was the wet season? (year 2, as rearing juv.) | w2\_Wet\_BFL\_Mag\_50 |
| d1\_DS\_Tim, f1\_recon\_20, f1\_recon\_40, d1\_DS\_Dur\_WS, d1\_DS\_Mag\_50 | How dry was the dry season? (pre-spawning) | d1\_DS\_Mag\_50 |
| w2\_Wet\_Tim, d2\_DS\_Dur\_WS, f2\_FA\_Tim, w2\_Wet\_BFL\_Dur | Dry to wet season transition timing (as rearing juv.) | w2\_Wet\_Tim |
| w1\_Wet\_BFL\_Dur, w1\_Wet\_Tim, s1\_SP\_Tim | How long was the wet season (as eggs and fry) | w1\_Wet\_BFL\_Dur |
| f1\_FA\_Mag, f1\_FA\_Dif\_num | Fall pulse magnitude (parents' spawning) | f1\_FA\_Dif\_num |
| f2\_FA\_Mag, f2\_FA\_Dif\_num | Fall pulse magnitude (rearing juv.) | f2\_FA\_Dif\_num |

## 6.1 Groups 1 and 2

These metrics describe the magnitude and timing of wet-season flows (years 1 and 2), effectively characterized by the question, ‘how wet was the wet season?’ We selected w1\_Wet\_BFL\_Mag\_50 and w2\_Wet\_BFL\_Mag\_50 as the most conceptually central metric to represent the amount of water passing through the watershed during two wet seasons: w1, the first wet season, experienced by a cohort as eggs and newly-hatched alevin and fry, and w2, experienced by the cohort as overwintering parr.

## 6.2 Group 3

These metrics describe the magnitude and timing of dry-season flows before the cohort’s spawning. We selected d1\_DS\_Mag\_50 as the most conceptually central metric to represent the amount of water passing through the watershed during the dry season before a cohort’s parents’ spawning.

## 6.3 Groups 4 and 5

These metrics quantify the timing of the wet season onset and duration (year 2). We selected w2\_Wet\_Tim, the timing of the onset of the second wet season, and w2\_Wet\_BFL\_Dur, the duration of wet season baseflow, to characterize the timing of the wet season experienced by a cohort of coho as overwintering juveniles.

## 6.4 Groups 6 and 7

These metrics quantify the magnitude of the fall pulse flow (years 1 and 2). We selected the fall flow increase FA\_dif\_num (from **Baruch2024?**) for both years, as it is the only fall flows magnitude metric occurring in every water year, with no missing values.

# 7 Ecological Data Features

## 7.1 Sources and methods

Table 4: Description and source information for ecological observations of the two salmonid species of concern.

| Obs. ID | Abbrev. | Description | Monitoring Details | Source(s) | Predictor Seasons |
| --- | --- | --- | --- | --- | --- |
| A | coho\_spawner\_abundance | Num. coho spawners (escapement) | Scott River Fish Counting Facility | Knechtle and Guidice 2023, CDFW | d1, f1, w1 |
| B | coho\_redds\_in\_brood | Num. obs. coho redds | Spawning ground surveys | Sources in Section 3.2 | d1, f1, w1, s1 |
| C | coho\_smolt\_abun\_est | Est. num. coho smolt | Rotary Screw Trap | Romero and Robinson, 2023 | d1, f1, w1, s1, d2, f2, w2, s2 |
| D | chinook\_spawner\_abundance | Num. Chinook spawners (escapement) | Scott River Fish Counting Facility | Knechtle and Guidice 2023, CDFW | d1, f1, w1 |
| E | chinook\_spawner\_old\_method (NOT USED in this analysis) | Num. Chinook spawners (escapement) | Temporary fish marking weir, 1985-1991; capture-recapture method, 1992-2012; video fish counting facility post-2012 | Knechtle and Chesney 2012 | d1, f1, w1 |
| F | chinook\_juvenile\_abundance | Num. Chinook juveniles | Rotary Screw Trap | Romero and Robinson, 2023 | d1, f1, w1, s1 |
| -- | coho\_smolt\_per\_fem | Coho smolt per fem. spawner | Ratio (C/A) for relevant cohort | Knechtle and Guidice 2023, CDFW | d1, f1, w1, s1, d2, f2, w2, s2 |
| -- | chinook\_juv\_per\_adult | Chinook juv. per adult | Ratio (F/D) for relevant cohort | Knechtle and Guidice 2023, CDFW | d1, f1, w1, s1 |

## 7.2 Autocorrelation in ecological records

Autocorrelation, with a lag of 3, is evident in two ecological records: the abundances of coho redds and coho smolt (Figure 4). In other words, the 3-year-lagged record of coho smolt approaches, and for redds exceeds, the 95% confidence interval that it is not random noise.

Interestingly, for coho spawner abundance, although the sign of the autocorrelation is positive at 3 and 6 year lags (which we would expect, reflecting the cohort structure), autocorrelation in the coho spawner record is weaker than in the redd and smolt records.

No significant autocorrelation is evident in the three Chinook data types, and none is observed for coho smolt per female.

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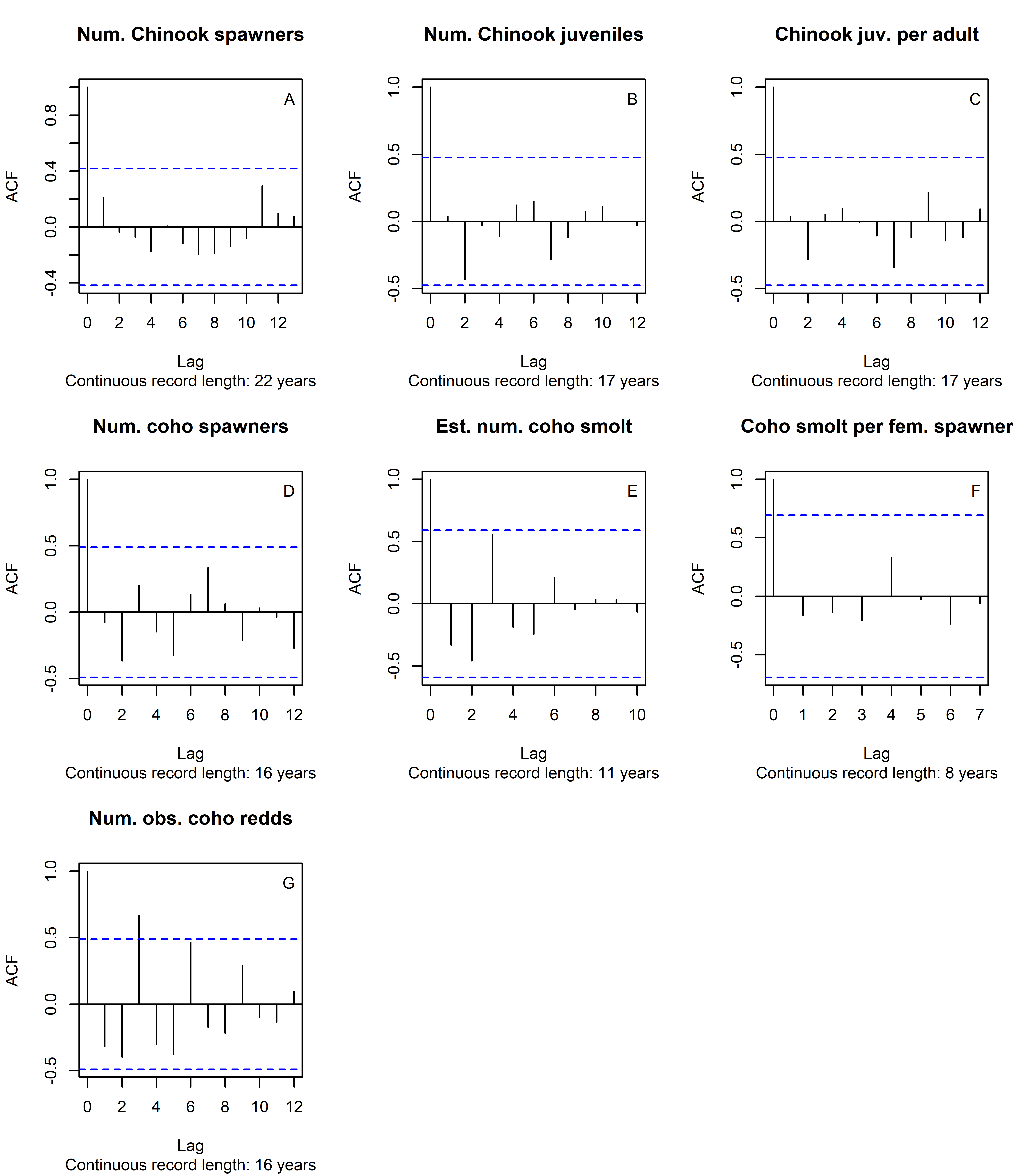


Figure 4: Autocorrelation function estimates for all available ecological outcome records.

# 8 Statistical Method Details

## 8.1 LASSO regression

### 8.1.1 Equation

LASSO (Least Absolute Shrinkage and Selection Operator) regression minimizes the following quantity:

Where:

* is the number of ecological observations;
* enumerates the brood years;
* is the number of predictors;
* enumerates the hydrologic predictors;
* is the observed value of hydrologic predictor for brood year (independent variable);
* is the observed value of ecological response in the salmon cohort with brood year (dependent variable);
* is the intercept value for the resulting linear model;
* is the coefficient value for hydrologic predictor in the resulting linear model; and
* is a tuning parameter, referred to as a shrinkage penalty.

In this formulation, sufficiently large values of lambda generally shrink the values of all coefficients to 0 (the infinite-lambda case). The infinite-lambda case produces a model consisting solely of the intercept term, which takes on a value that is the average of all the observed values. Conversely, sufficiently small values of will produce linear models incorporating information from many predictors. The selection of the appropriate value is a critical step in the regression procedure, and is best done using cross-validation within the training dataset (James et al. 2013).

### 8.1.2 LASSO results: juvenile abundance on hydrologic metrics and spawner abundance

For purposes of statistical model comparison, we predicted juvenile abundance of coho and Chinook based on a predictor set that included Z-scored hydrologic metrics as well as Z-scored spawner abundances.

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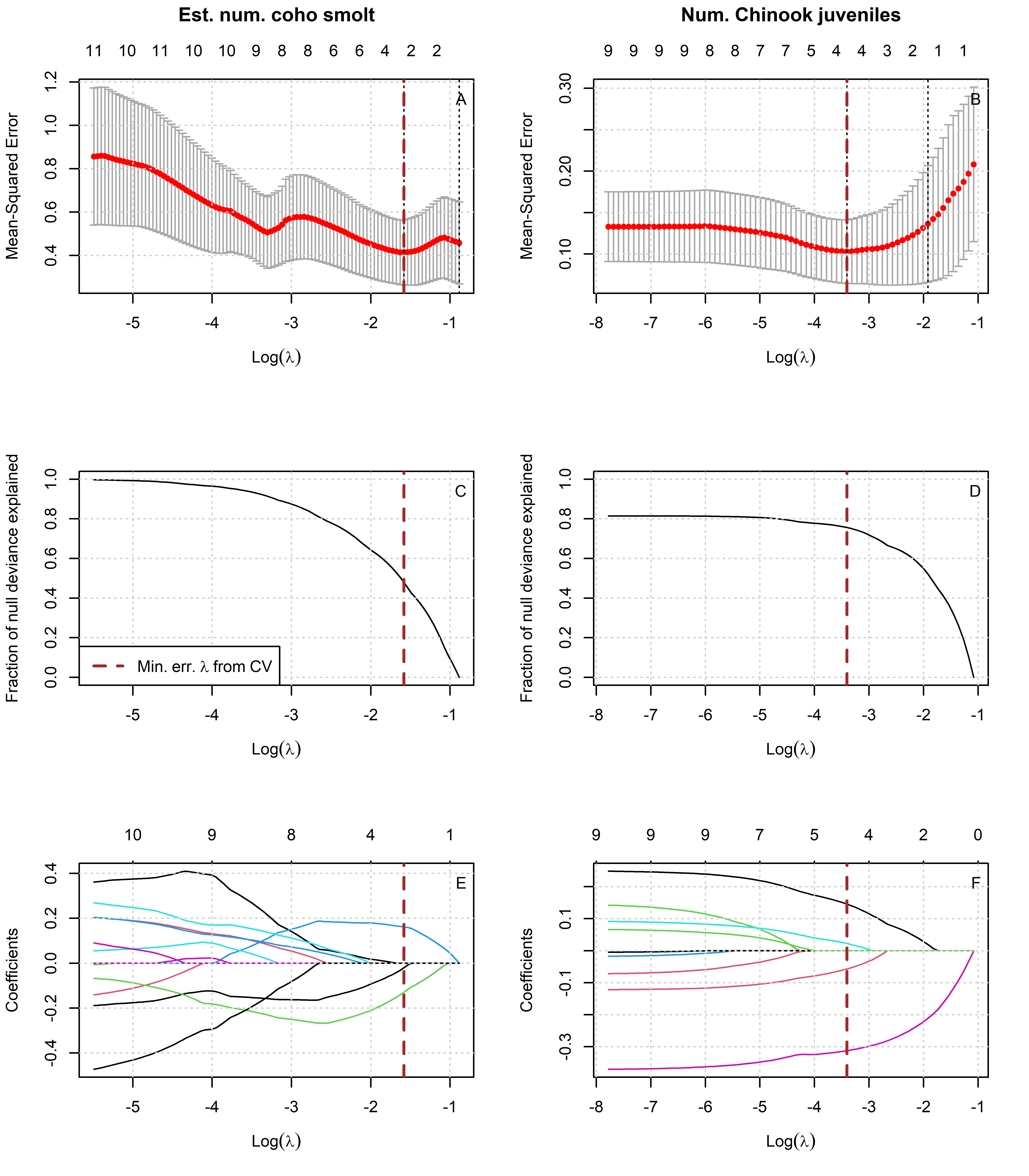


Figure 5: Results of lasso regression to predict log-transformed coho and Chinook outcomes with Z-scored hydrologic metrics. Models with more coefficients explain a greater fraction of deviance in the dataset (middle panel), but also produce higher test errors (top panel), indicating some overfitting at lower lambda values. Higher values of lambda tend to shrink the absolute values of regression coefficients toward 0 (bottom panel).

Table 5: Values for the intercept and coefficient terms in the Hydrologic Benefit function for estimated coho\_smolt\_abun\_est, including a description of which phenomena are associated with higher ecological outcome values.

| Predictor | Value | Greater Hydrologic Benefit value associated with |
| --- | --- | --- |
|  | 3.872 | (Intercept) |
| f1\_FA\_Dif\_num | 0.162 | Larger fall flow increase (during parents' spawning) |
| f2\_FA\_Dif\_num | -0.130 | Smaller fall flow increase (as juvenile fish) |
| s1\_SP\_ROC | -0.020 | Slower rate of change, spring recession (as recent hatchlings) |

Table 6: Values for the intercept and coefficient terms in the Hydrologic Benefit function for estimatedchinook\_juvenile\_abundance, including a description of which hydrologic phenomena are associated with higher ecological outcome values.

| Predictor | Value | Greater Hydrologic Benefit value associated with |
| --- | --- | --- |
|  | 5.443 | (Intercept) |
| w1\_Wet\_BFL\_Mag\_50 | -0.312 | Lower wet season baseflows (as eggs and hatchlings) |
| chinook\_spawners\_zscored | 0.146 | Abundance of spawners (parents of designated cohort) |
| s1\_SP\_ROC\_Max | -0.057 | Slower max. rate of change, spring recession (as outmigrating smolt) |
| w1\_Wet\_BFL\_Dur | 0.023 | Longer wet season baseflow duration (as eggs and hatchlings) |

### 8.1.3 LASSO results: juvenile abundance on hydrologic metrics only

For purposes of statistical model comparison, we predicted juvenile abundance of coho and Chinook based on a predictor set that included only Z-scored hydrologic metrics.

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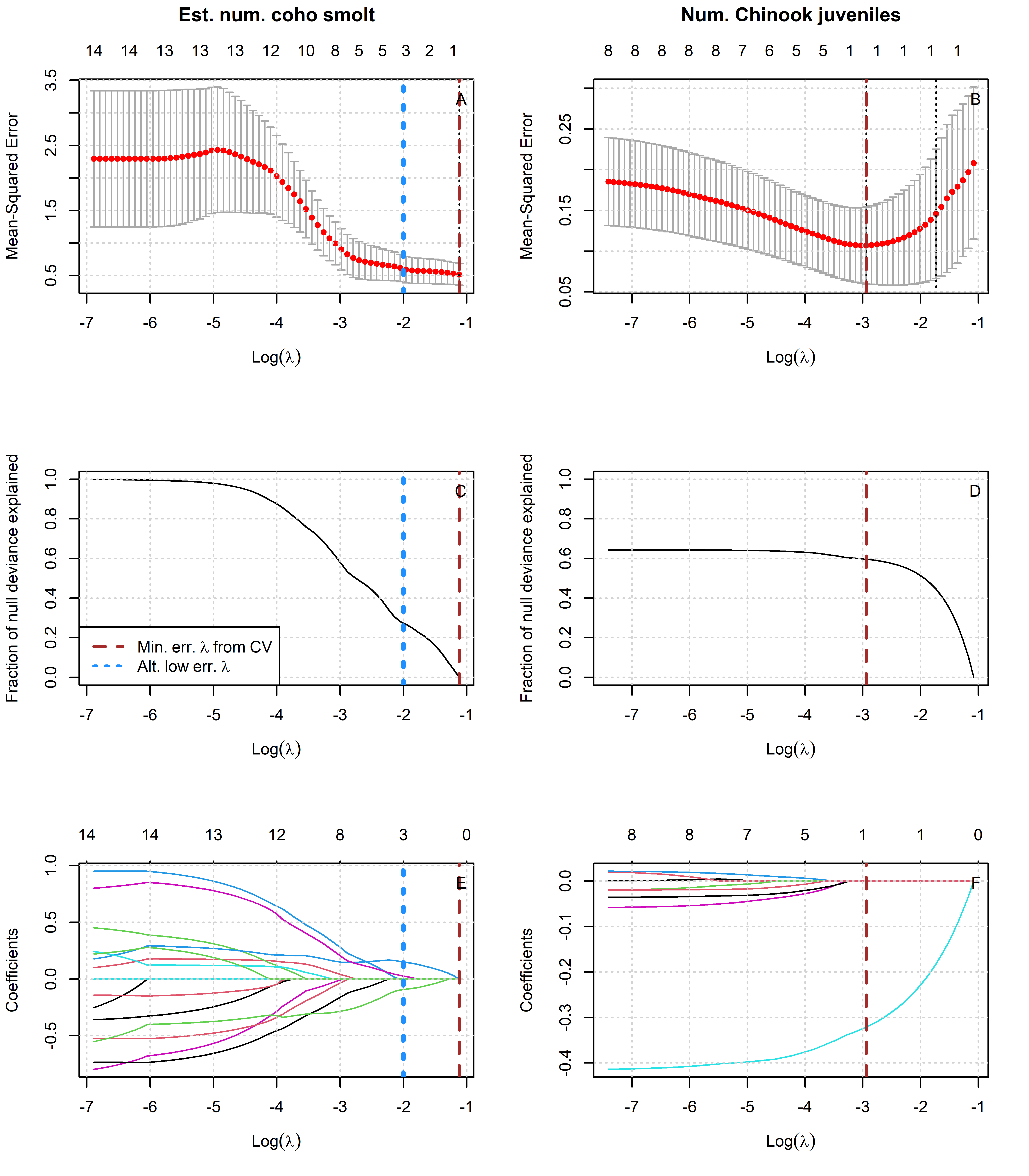


Figure 6: Results of lasso regression to predict log-transformed coho and Chinook outcomes with Z-scored hydrologic metrics. Models with more coefficients explain a greater fraction of deviance in the dataset (middle panel), but also produce higher test errors (top panel), indicating some overfitting at lower lambda values. Higher values of lambda tend to shrink the absolute values of regression coefficients toward 0 (bottom panel).

Table 7: Values for the intercept and coefficient terms in the Hydrologic Benefit function for estimated coho smolt abundance based on hydrology only, including a description of which phenomena are associated with higher ecological outcome values.

| Predictor | Value | Greater Hydrologic Benefit value associated with |
| --- | --- | --- |
|  | 3.903 | (Intercept) |
| f1\_FA\_Dif\_num | 0.151 | Larger fall flow increase (during parents' spawning) |
| f2\_FA\_Dif\_num | -0.093 | Smaller fall flow increase (as juvenile fish) |
| s2\_SP\_ROC | 0.027 | Faster rate of change, spring recession (as outmigrating smolt) |

Table 8: Values for the intercept and coefficient terms in the Hydrologic Benefit function for estimatedChinook juv. abundance based on hydrology only, including a description of which hydrologic phenomena are associated with higher ecological outcome values.

| Predictor | Value | Greater Hydrologic Benefit value associated with |
| --- | --- | --- |
|  | 5.449 | (Intercept) |
| w1\_Wet\_BFL\_Mag\_50 | -0.321 | Lower wet season baseflows (as eggs and hatchlings) |

## 8.2 MARSS Models

Multi-variate autoregressive state-space (MARSS) models are often used to model time series data (in which )

### 8.2.1 MARSS models of juveniles per spawner, single hydrologic covariate

For purposes of statistical model comparison, we calculated multiple MARSS models (15 for coho and 8 for Chinook) that predicted the observed ratio of juveniles-per-spawner for coho and Chinook based on a single Z-scored hydrologic metric.

Table 9: Each row corresponds to a MARSS model predicting the time series of coho spf observations using itself (up to time t) and one hydrologic metric covariate. Coefficient sign and value indicate the direction and strength of the influence of the hydrologic metric; i.e., a negative coefficient for hydrologic metric f1\_recon\_120 indicates that an earlier first fall river reconnection (120 cfs) is associated with a greater coho spf value. Models are listed in order from best (lowest AICc value) to worst. Values marked with -- indicate that gaps in the time series for the hydrologic metric prevented the calculation of a model using that covariate.

| Covariate | Coefficient | AICc |
| --- | --- | --- |
| f1\_recon\_120 | -0.403 | 21.24 |
| f1\_FA\_Dif\_num | 0.306 | 23.13 |
| w1\_Wet\_BFL\_Mag\_50 | 0.136 | 26.46 |
| d1\_DS\_Mag\_90 | 0.102 | 27.05 |
| s2\_SP\_ROC\_Max | -0.093 | 27.34 |
| f2\_recon\_120 | -0.173 | 27.5 |
| s2\_SP\_ROC | 0.085 | 27.55 |
| d1\_DS\_Mag\_50 | -0.109 | 27.74 |
| w2\_Wet\_BFL\_Mag\_50 | 0.085 | 27.93 |
| s1\_SP\_ROC\_Max | 0.046 | 28.25 |
| s2\_SP\_Tim | 0.029 | 28.26 |
| w2\_Wet\_Tim | -0.023 | 28.47 |
| f2\_FA\_Dif\_num | 0.036 | 28.5 |
| s1\_SP\_ROC | 0.007 | 28.55 |
| w1\_Wet\_BFL\_Dur | 0.003 | 28.55 |
| f1\_FA\_Dur | -- | -- |
| f1\_FA\_Tim | -- | -- |
| f2\_FA\_Dur | -- | -- |

Table 10: Each row corresponds to a MARSS model predicting the time series of Chinook jpa observations using itself (up to time t) and one hydrologic metric covariate. Coefficient sign and value indicate the direction and strength of the influence of the hydrologic metric; i.e., a negative coefficient for hydrologic metric f1\_recon\_120 indicates that an earlier first fall river reconnection (120 cfs) is associated with a greater Chinook jpa value. Models are listed in order from best (lowest AICc value) to worst. Values marked with -- indicate that gaps in the time series for the hydrologic metric prevented the calculation of a model using that covariate.

| Covariate | Coefficient | AICc |
| --- | --- | --- |
| d1\_DS\_Mag\_90 | 0.069 | 28.91 |
| s1\_SP\_ROC\_Max | -0.057 | 29.17 |
| f1\_recon\_120 | -0.039 | 29.61 |
| w1\_Wet\_BFL\_Dur | -0.019 | 29.7 |
| d1\_DS\_Mag\_50 | -0.039 | 29.72 |
| w1\_Wet\_BFL\_Mag\_50 | 0.031 | 29.74 |
| f1\_FA\_Dif\_num | -0.013 | 29.88 |
| s1\_SP\_ROC | 0.002 | 29.89 |
| f1\_FA\_Dur | -- | -- |
| f1\_FA\_Tim | -- | -- |

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## 2

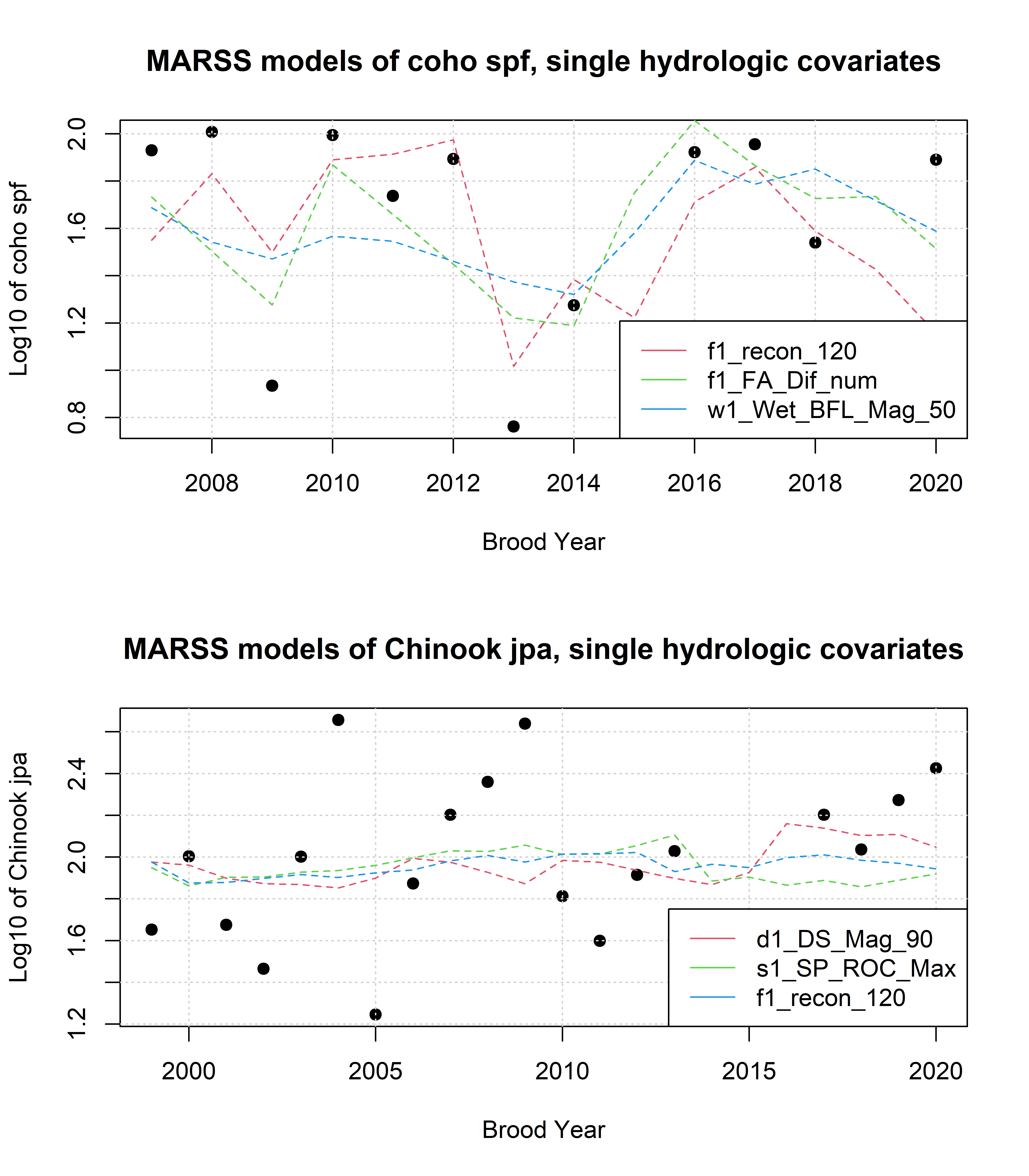


Figure 7: Results of the three best single-hydrologic-covariate MARSS models to predict log-transformed Chinook and coho juvenile-per-spawners ratios with Z-scored hydrologic metrics.

### 8.2.2 MARSS models of juveniles abundance, single hydrologic covariate

For purposes of statistical model comparison, we calculated multiple MARSS models (15 for coho and 8 for Chinook) that predicted juvenile abundance for coho and Chinook based on a single Z-scored hydrologic metric.

Table 11: Each row corresponds to a MARSS model predicting the time series of coho smolt abundance observations using itself (up to time t) and one hydrologic metric covariate. Coefficient sign and value indicate the direction and strength of the influence of the hydrologic metric; i.e., a negative coefficient for hydrologic metric f1\_recon\_120 indicates that an earlier first fall river reconnection (120 cfs) is associated with a greater coho smolt abundance value. Models are listed in order from best (lowest AICc value) to worst. Values marked with -- indicate that gaps in the time series for the hydrologic metric prevented the calculation of a model using that covariate.

| Covariate | Coefficient | AICc |
| --- | --- | --- |
| f1\_FA\_Dif\_num | 0.206 | 40.37 |
| f2\_FA\_Dif\_num | -0.136 | 41.55 |
| w2\_Wet\_BFL\_Mag\_50 | 0.08 | 41.74 |
| d1\_DS\_Mag\_90 | 0.058 | 41.78 |
| s1\_SP\_ROC\_Max | 0.061 | 41.78 |
| s2\_SP\_ROC\_Max | 0.06 | 41.8 |
| w1\_Wet\_BFL\_Mag\_50 | 0.059 | 41.83 |
| s2\_SP\_ROC | 0.045 | 41.83 |
| w2\_Wet\_Tim | 0.039 | 41.88 |
| s1\_SP\_ROC | -0.017 | 41.98 |
| f1\_recon\_120 | -0.035 | 41.98 |
| w1\_Wet\_BFL\_Dur | 0.013 | 41.99 |
| d1\_DS\_Mag\_50 | -0.015 | 42.01 |
| f2\_recon\_120 | -0.018 | 42.01 |
| s2\_SP\_Tim | -0.002 | 42.02 |
| f1\_FA\_Dur | -- | -- |
| f1\_FA\_Tim | -- | -- |
| f2\_FA\_Dur | -- | -- |

Table 12: Each row corresponds to a MARSS model predicting the time series of Chinook juv. abundance observations using itself (up to time t) and one hydrologic metric covariate. Coefficient sign and value indicate the direction and strength of the influence of the hydrologic metric; i.e., a negative coefficient for hydrologic metric f1\_recon\_120 indicates that an earlier first fall river reconnection (120 cfs) is associated with a greater Chinook juv. abundance value. Models are listed in order from best (lowest AICc value) to worst. Values marked with -- indicate that gaps in the time series for the hydrologic metric prevented the calculation of a model using that covariate.

| Covariate | Coefficient | AICc |
| --- | --- | --- |
| w1\_Wet\_BFL\_Mag\_50 | -0.135 | 32.65 |
| s1\_SP\_ROC\_Max | -0.106 | 33.11 |
| d1\_DS\_Mag\_50 | 0.089 | 34.36 |
| f1\_recon\_120 | -0.062 | 34.5 |
| w1\_Wet\_BFL\_Dur | 0.032 | 34.64 |
| f1\_FA\_Dif\_num | -0.053 | 34.85 |
| s1\_SP\_ROC | 0.007 | 35.06 |
| d1\_DS\_Mag\_90 | -0.006 | 35.08 |
| f1\_FA\_Dur | -- | -- |
| f1\_FA\_Tim | -- | -- |

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## 2

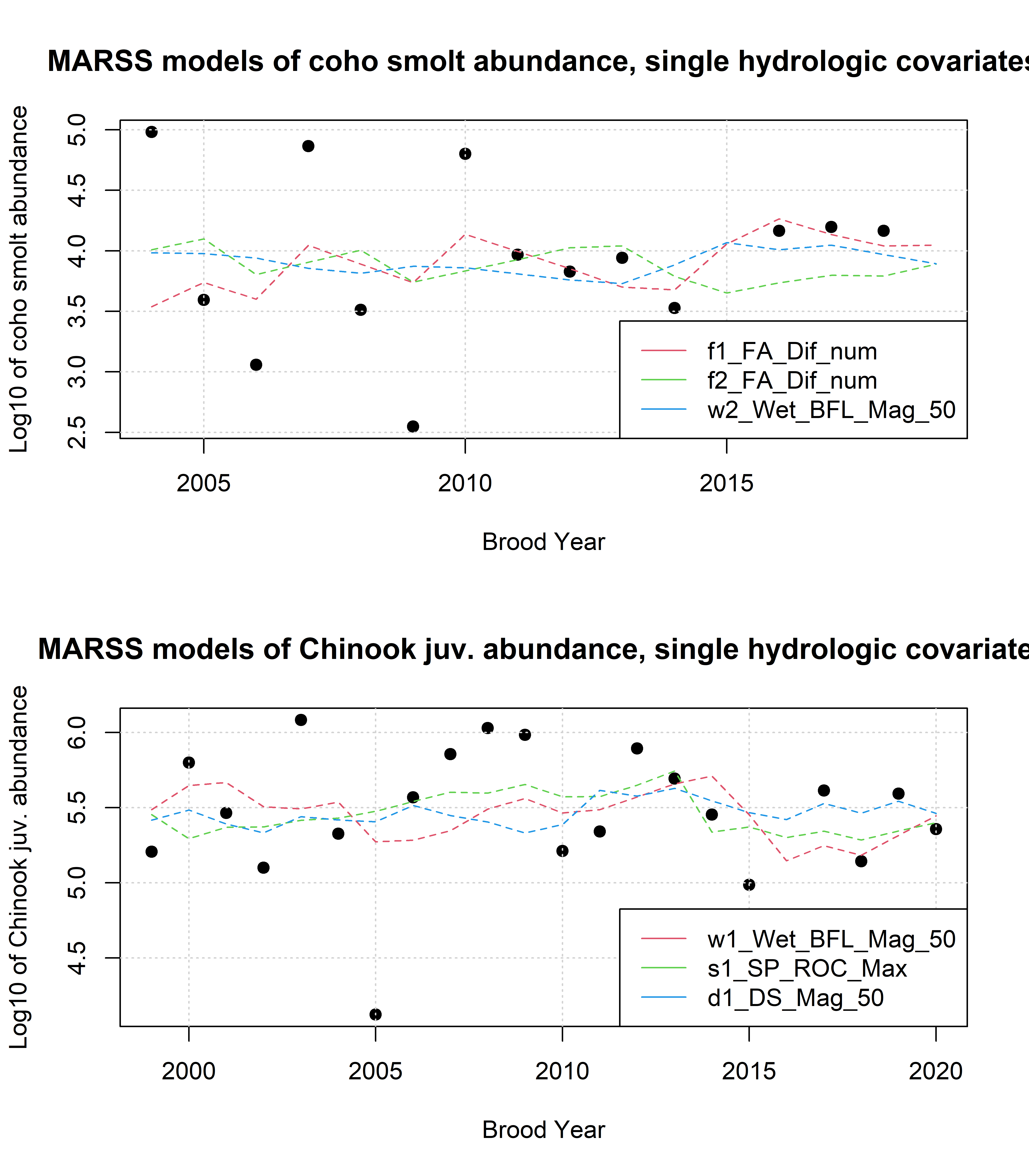


Figure 8: Results of the three best single-hydrologic-covariate MARSS models to predict log-transformed Chinook and coho outcomes with Z-scored hydrologic metrics.

### 8.2.3 MARSS models of juvenile abundance, two covariates (spawner abundance and one hydrologic)

For purposes of statistical model comparison, we calculated multiple MARSS models (15 for coho and 8 for Chinook) that predicted juvenile abundance for coho and Chinook based on a single Z-scored hydrologic metric and Z-scored parental spawner abundance; thus, coefficients were calculated for both the hydrology and spawner covariates.

| Hydrologic Covariate | AICc | Hydro Coef. | Spawner Coef. | HtoSratio |
| --- | --- | --- | --- | --- |
| f1\_FA\_Dif\_num | 32.11 | 0.550 | 0.374 | 1.5 |
| f1\_recon\_120 | 37.67 | -0.605 | 0.452 | -1.3 |
| d1\_DS\_Mag\_90 | 38.16 | 0.229 | 0.338 | 0.7 |
| w1\_Wet\_BFL\_Mag\_50 | 38.27 | 0.245 | 0.301 | 0.8 |
| f2\_recon\_120 | 40.62 | -0.237 | 0.161 | -1.5 |
| w2\_Wet\_BFL\_Mag\_50 | 41.18 | 0.110 | 0.201 | 0.5 |
| s1\_SP\_ROC | 41.32 | -0.065 | 0.160 | -0.4 |
| s1\_SP\_ROC\_Max | 41.50 | 0.052 | 0.186 | 0.3 |
| w2\_Wet\_Tim | 41.50 | 0.049 | 0.176 | 0.3 |
| d1\_DS\_Mag\_50 | 41.61 | 0.045 | 0.164 | 0.3 |
| f2\_FA\_Dif\_num | 41.65 | -0.040 | 0.160 | -0.2 |
| s2\_SP\_ROC | 41.66 | 0.017 | 0.169 | 0.1 |
| s2\_SP\_Tim | 41.67 | -0.010 | 0.159 | -0.1 |
| w1\_Wet\_BFL\_Dur | 41.67 | 0.010 | 0.167 | 0.1 |
| s2\_SP\_ROC\_Max | 41.68 | -0.004 | 0.167 | 0.0 |
| f1\_FA\_Dur |  |  |  |  |
| f1\_FA\_Tim |  |  |  |  |
| f2\_FA\_Dur |  |  |  |  |

| Hydrologic Covariate | AICc | Hydro Coef. | Spawner Coef. | HtoS\_ratio |
| --- | --- | --- | --- | --- |
| s1\_SP\_ROC\_Max | 36.03 | -0.116 | 0.0573 | -2.0 |
| w1\_Wet\_BFL\_Mag\_50 | 36.06 | -0.132 | 0.0209 | -6.3 |
| f1\_recon\_120 | 37.77 | -0.062 | 0.0361 | -1.7 |
| d1\_DS\_Mag\_50 | 37.81 | 0.081 | 0.0183 | 4.4 |
| w1\_Wet\_BFL\_Dur | 37.84 | 0.035 | 0.0426 | 0.8 |
| f1\_FA\_Dif\_num | 38.18 | -0.046 | 0.0318 | -1.4 |
| s1\_SP\_ROC | 38.19 | 0.021 | 0.0528 | 0.4 |
| d1\_DS\_Mag\_90 | 38.35 | 0.004 | 0.0378 | 0.1 |
| f2\_recon\_120 |  |  |  |  |
| f1\_FA\_Dur |  |  |  |  |
| f1\_FA\_Tim |  |  |  |  |
| f2\_FA\_Dur |  |  |  |  |
| f2\_FA\_Dif\_num |  |  |  |  |
| w2\_Wet\_BFL\_Mag\_50 |  |  |  |  |
| w2\_Wet\_Tim |  |  |  |  |
| s2\_SP\_ROC |  |  |  |  |
| s2\_SP\_ROC\_Max |  |  |  |  |
| s2\_SP\_Tim |  |  |  |  |

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## 2

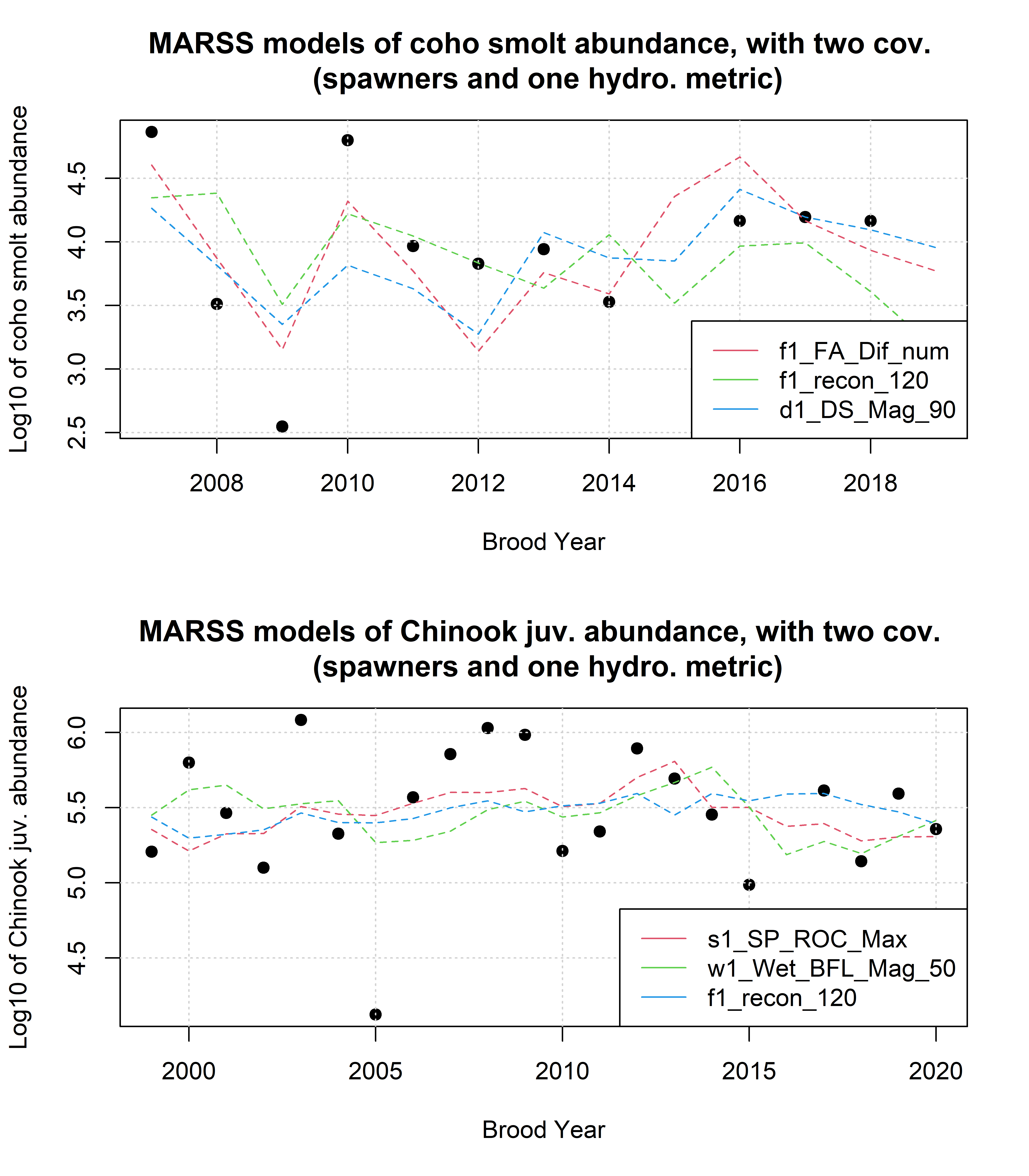


Figure 9: Results of MARSS to predict log-transformed juvenile abundance for coho and Chinook outcomes with Z-scored hydrologic metrics plus spawner data.

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