In-season forecasting of Fraser Chinook Salmon using genetic stock identification of test fishery data

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Abstract

In-season methods that produce accurate and timely forecasts of returning salmon abundances allow fisheries managers to alter fishing plans in order to meet conservation and harvest objectives. In-season methods are challenged by variability in catch statistics due to factors external to abundance, specifically, fluctuations in the migration timing of target and co-migrating stocks. I apply genetic stock identification (GSI) data to develop catch indices for the five Fraser Chinook management units, and use these indices to forecast returns for each management unit according to four in-season model forms. I evaluate models using three performance measures to determine forecasting errors. Results show that forecasts for Spring 5_2 and Summer 5_2 Chinook can be produced with reasonable accuracy early in the fishing season. Forecasts of Spring 4_2, Summer 4_1, and Fall Chinook are less accurate. Results indicate that this technique shows promise for providing accurate and timely forecasts for the five Fraser Chinook management units, particularly as additional years of data are GSI-analyzed.

Keywords: Fraser Chinook; in-season forecasting; catch indices; model evaluation

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1. Introduction

Salmon fishery managers are challenged by conflicting objectives to conserve biodiversity (Beacham et al. 2014b) while allowing for harvest of good-quality fish by multiple sectors (Shaklee et al. 1999, Su and Adkison 2002, Parken et al. 2008, Beacham et al. 2014b). To attain these objectives, stocks must be harvested at individually sustainable rates, with harvests distributed over the course of the migration of each stock (Hyun et al. 2005, Flannery et al. 2010). This is difficult to attain, as most fisheries intercept multiple stocks at a time, and those stocks often vary in their target harvest rates (Shaklee et al. 1999, Beacham et al. 2004b, Price et al. 2008, Satterthwaite et al. 2015). In order to design fisheries that are compatible with mixed-stocks, managers require accurate estimates of returning population abundances and their migration timing prior to their migration through fishing areas (Marshall et al. 1987, Springborn et al. 1998, Zheng and Mathisen 1998, Hyun et al. 2005, DFO 2016).

Accurate estimates of returning abundances allow managers to determine appropriate harvest rates for each fishing sector (Springborn et al. 1998), allocating catch when surpluses exist, or imposing closures when abundances are below target (Fried and Hilborn 1988, Claytor 1996, Pestal 2006). Where data are available, forecasts are produced prior to the fishing season, using biological stock-recruitment models, time-series average, or sibling models (Haeseker et al. 2008, Grant et al. 2010). However, pre-season forecasts are often associated with large amounts of error, which can lead to missed fishing opportunities or management targets, potentially impacting conservation concerns (Walters and Buckingham 1975, Quinn and Marshall 1989, Su and Adkison 2002, Holt and Peterman 2006, Haeseker et al. 2008). During the fishing season, in-season forecasts are used to adjust management plans once fish begin to enter their natal rivers or approach areas (Sprout and Kadowaki 1987). In-season forecasts use intercepting commercial or test fishery data in the form of catch-per-unit (CPUE) indices to predict returning abundances based on their historical relationship, through regression models or ratios (Walters and Buckingham 1975, Minard and Meacham 1987, Dempson et al. 1998, Flynn and Hilborn 2004, Flynn et al. 2006, Catalano and Jones 2014). In-season methods have become increasingly relied upon, and are generally considered more dependable as indicators of abundance than pre-season methods, due to uncertainty and poor performance of preseason forecasts in the past (Walters and Buckingham 1975, Henderson et al. 1987, Claytor 1996, Haeseker et al. 2008, Holt et al. 2009).

Ideally in-season forecasts are produced on a daily, weekly, or monthly basis to inform harvest decisions through iterative processes (Fried and Hilborn 1988, Hyun et al. 2005). However, forecasts are often produced only once during the fishing season, to update pre-season estimates, or to be used as stand-alone forecasts (Fried and Hilborn 1988, Zheng and Mathisen 1998, Flynn and Hilborn 2004, Chamberlain and Parken 2012). In such cases, timing of forecast availability is very important (Claytor 1996). In-season estimates are increasingly important as the fishing season progresses and data become more informative (Catalano and Jones 2014). Conversely, they are most beneficial early in the fishing season when managers have the greatest flexibility to adjust fisheries (Hyun et al. 2005, Chamberlain and Parken 2012). Managers must have adequate time to close fisheries when in-season forecasts indicate lower than expected abundances, or to allow enough fishing time when abundances are larger than expected (Holt and Peterman 2006). However, uncertainty in early season forecasts can translate into failure to meet the objectives of the fishery management system (Zheng and Mathisen 1998, Catalano and Jones 2014).

In-season forecasting methods are challenged by annual variations in the migration timing of forecasted and co-migrating populations. Most in-season methods rely on the assumption of average migration timing, relating historical catch statistics to annual or reconstructed in-season returns (Walters and Buckingham 1975, Minard and Meacham 1987, Woodey 1987, Fried and Hilborn 1988, Zheng and Mathisen 1998, Hyun et al. 2005, Chamberlain and Parken 2012, Catalano and Jones 2014). Although authors such as Keefer et al. (2004) have found that migratory timing of individual stocks is consistent enough to be predictable, it remains widely acknowledged that migration timing can vary greatly on an inter-annual basis (Zheng and Mathisen 1998). Variability in migration timing causes catch statistics to deviate from average values for a given date and abundance. This can be misinterpreted as an indication of run size, and leads to over- or under- forecasting when using average timing models (Zheng and Mathisen 1998, Flynn and Hilborn 2004, Hyun et al. 2005). For example, larger than average catches early in the season can incorrectly indicate a large return when in fact the return is early, and therefore more of the run is available to fisheries than average on a given date (Flynn and Hilborn 2004).

In areas where stocks mix, such as large river systems with multiple populations of a given species, run timing of co-migrating stocks adds to the variability in catch indices. Migration timing of returning salmon populations can differ greatly, even within a species (Keefer et al. 2004, Parken et al. 2008, Chamberlain and Parken 2012). In contrast, timing can also greatly overlap, as in the case of Fraser Chinook, where return timing of the Spring 5_2[1] and Summer 5_2 stock groups overlaps with both Spring 4_2 and Summer 4_1 Chinook (Chamberlain and Parken 2012). Such overlaps lead to high catch index variability because catch rates reflect fluctuations in both abundances and return timing of multiple stocks.

Variability in catch indices leads to uncertainty in subsequent run size predictions (Marshall et al. 1987, Zheng and Mathisen 1998, Hyun et al. 2005, Catalano and Jones 2014). Early in the fishing season, variability in catch indices is particularly problematic (Springborn et al. 1998), hence early in-season data may not give a clear signal of run size (Chamberlain and Parken 2012). Removal of some of the uncertainty in catch indices by including covariates in in-season models, or by stratifying CPUE according to major sources of variation, can improve forecasting ability (Marshall et al. 1987).

[1] Stock aggregates are referred to using the Gilbert-Rich naming convention, whereby the large number indicates the age at maturity of the majority of the population, and the subscript represents the number of winters spent in freshwater before migrating to the ocean (DFO 2011a). Stock groups consist of individuals with varying age structures, though they have been named according to the predominant life history.

For Pink Salmon in Southeastern Alaska, in-season forecasts have been improved by including covariates in the form of sex ratios, as an indicator of migration timing (Zheng and Mathisen 1998). For Port Moller Sockeye, the main causes of variability in test fishery indices are fluctuations in age structure combined with unequal vulnerability of age classes to fishing gear (Flynn and Hilborn 2004). Predictive ability of in-season forecasts for Port Moller Sockeye improved when age composition, migration route, and a proxy for migration timing were included in models as covariates. External sources of variability have also been successfully used to stratify catch indices. Fish age and river of origin accounted for approximately half the variation in Lynn Canal Sockeye commercial CPUE indices that was not attributed to migration timing (Marshall et al. 1987). Variability in catch indices was significantly reduced when indices were stratified by age and stock, using scale pattern analysis, resulting in more accurate in-season forecasting methods (Marshall 1987).

In this study I apply genetic stock identification (GSI) assignments to stratify test fishery catch indices for Fraser River Chinook Salmon into stock aggregates used for their management. I apply these indices to develop in-season forecasting models for each aggregate, and evaluate potential model forms to identify those that perform best for each aggregate in terms of the accuracy of forecasts, and subsequently, the timing of their availability. For two stock aggregates I evaluate models against currently used CPUE-based in-season forecasting methods to quantify potential improvements in forecasting due to CPUE stratification. I further use the performance of the current in-season methods as guidelines for evaluating the accuracy of models for all management groups.

Fraser Chinook present a good case study to assess GSI-derived indices as in-season predictors for several reasons. First, Fraser Chinook management units have experienced diverging trends in abundance over the past decade, creating the potential for increased harvest of some stocks, and a need for conservation of others. Availability of forecasts at the management unit level prior to fisheries will present opportunities to plan fisheries according to returning abundances, increasing the potential to meet management objectives. Second, Fraser Chinook are currently managed with a test fishery-based in-season model for Spring and Summer 5_2 Chinook, the predictions of which are used to determine in-season management actions to protect these stock groups. This model acts as a basis of comparison for those developed here. Additionally, past research in developing the current model has provided groundwork for this analysis. In this respect, incorporating genetic methods to develop stock indices for Fraser Chinook has proven beneficial for predicting run size on the stock and stock aggregate level (Parken et al. 2008). However, the previous study was limited by data availability and did not explore the potential of these methods for in-season forecasting (Parken et al. 2008).

1.1. Fraser River Chinook

The Fraser River is the largest producer of Chinook Salmon in Canada (Bailey et al. 2001, Parken et al. 2008), contributing to commercial, recreational, and First Nations fisheries in the Fraser River, Northern British Columbia, Southeastern Alaska, the west coast of Vancouver Island, and Washington State (Bailey et al. 2001, DFO 2006a, CTC 2015a).

Fraser Chinook stocks are divided into five management units based on their run timing and life history (DFO 2008). Run timing has been categorized into three groups for fishery management: Spring, Summer, and Fall (Fraser et al. 1982, DFO 1999). Spring runs migrate through the lower Fraser River with at least 50% of their returning abundance passing through prior to July 15 (median migration date). Two management units have Spring timing. The Spring 4_2 stocks enter the Fraser River from early March to the end of July, with a median migration date past the Albion test fishery in mid-July, and the Spring 5_2 stocks have an earlier median migration date, in late June (Figure 1) (Beacham et al. 2003b, DFO 2011a). The two summer management units, Summer 5_2 and Summer 4_1 peak in their migrations through the lower river between July 15th and September 1st, with the median migration date of the Summer 5_2 populations falling in late July, and that of the Summer 4_1 management unit falling in mid-August (Figure 1).

The Fall run migrates after September 1st, with most populations migrating through the lower Fraser between mid-September and mid-October, reaching their median migration date in mid-September (Figure 1) (Bailey et al. 2001, Beacham et al. 2003b, Parken et al. 2008, DFO 2011a).

Fraser Chinook management units have experienced different trends in their returns and escapements since the mid-1990's. The Fall run has maintained large abundances despite fluctuations, and the Summer 4_1 management unit has shown large increases in returns, in some years tripling pre-1995 abundances. Conversely, the Spring (Spring 4_2 and Spring 5_2) and Summer 5_2 groups have experienced multiple declines (Figure 2). After a high escapement in 1994, early-Spring components of the spring runs began to decline, triggering concerns over their abundances (Bailey et al. 2001). After another peak in escapement in 2003, abundances of these early-timed stocks again declined (DFO 2008, Chamberlain and Parken 2012).

Concern over the post-2003 decline in Spring 4_2, Spring 5_2 and Summer 5_2 escapements began mounting in 2006, and in 2008 Fisheries and Oceans Canada (DFO) designated these management units as conservation concerns (DFO 2008, 2009, Chamberlain and Parken 2012). In that year (2008), DFO, in consultation with stakeholders, designed and imposed restrictions aimed at reducing the exploitation of early-timed stocks by 50%, with the majority of reductions affecting commercial and recreational interests (DFO 2009). However, aside from the declining trend, the impetus behind heightened regulation in 2008 was the combination of an extremely low catch rate of Fraser Chinook by the Albion test fishery in the Spring of 2008, and recent work that identified a significant relationship between Albion test fishery catch rates and returns of Spring and Summer 5_2 Chinook (Dempson et al. 1998, DFO 2009, Chamberlain and Parken 2012). Today, in-season forecasts are produced for Spring and Summer 5_2 Chinook, using a model that has evolved from four studies conducted on this relationship.

Starr and Schubert (1990) and Dempson et al. (1998) initially investigated relationships between Albion test fishery indices and returning abundances of Fraser

Chinook. In Dempson et al. (1998), the authors' purpose was to identify significant associations between cumulative weekly indices and returns of early and late-timed Chinook. They found a significant relationship for the early-timed populations, though none for the later components (Dempson et al. 1998). Starr and Schubert (1990) looked at the relationship between test fishery indices and returns of Harrison Chinook, and found that they were poorly correlated. Subsequently, Parken et al. (2008) evaluated the relationship between annual cumulative test fishery indices and returns for stocks and stock aggregates of Fraser Chinook, using GSI data for 2000 and 2001 to derive stock-specific indices. They found that the addition of genetic information improved the association between test fishery indices and return abundances. Although relationships were stronger when stocks were aggregated according to run timing and regional reporting groups (Parken et al. 2008).

Building on the work of Dempson et al. (1998) and Parken et al. (2008), Chamberlain and Parken (2012) formally tested the applicability of test fishery indices for in-season management, relating weekly cumulative indices to total returns of combined Spring and Summer 5_2 Chinook from 1995-2008. They found significant relationships across multiple analysis weeks, starting in mid-May until late July. They did not apply GSI in their analysis due to limited data availability. The models developed by Chamberlain and Parken (2012) produced "modestly accurate and precise" estimates, which most recently have been associated with an average error of 17% (Chamberlain and Parken 2012, DFO 2013).

Since 2008, in-season forecasts generated from Albion test fishery catch rates have become the basis for Fraser Chinook in-season management decisions. Concurrently, management of Fraser Chinook has become increasingly complex, as more precise regulations have evolved to protect the Spring and Summer-run management units (DFO 2008, 2009, 2010, 2011a, 2012, 2015a, 2015b). Concerns over the Spring 4_2, Spring 5_2, and Summer 5_2 management units, and consequently the limited information available for other stock groups, have resulted in a management system for Fraser Chinook that is driven by these three stock groups (M. Maxwell, Fraser Chinook & Coho Management Biologist, DFO, pers. comm., April 11, 2016).

Objectives for the Spring 4_2 populations are to minimize incidental harvests in marine fisheries, and minimize direct harvest in Fraser River fisheries up to July 15th (DFO 2015a). For Spring and Summer 5_2 Chinook, objectives are to conserve populations, as defined by three tiers of regulations (Management Zones). Each tier, or Management Zone, is associated with a range of predicted return abundances, upon which regulations are designed with the aim of rebuilding Spring and Summer 5_2 escapements. DFO has identified five fisheries for regulation, based on their potential impacts on Spring and Summer 5_2 Chinook: Northern BC and WCVI commercial troll fisheries, Juan de Fuca and Fraser River recreational fisheries, and Fraser River First Nations' fisheries (DFO 2015a). Within these fisheries, DFO has designated management actions for the three Management Zones, with the most restrictive regulations coming into effect when the Spring and Summer 5_2 return estimate falls into Zone 1 and the least severe being imposed when the estimate is in Zone 3. Generally, managers begin the fishing season in Zone 1, and update this based on in-season information as it becomes available. Return forecasts are produced bi-weekly, from mid-May to mid-June, though management actions are only triggered by the mid-June update, which in previous years has been between June 13th and 18th (2010-2013) (DFO 2011b, 2012, 2014; M. Maxwell, pers. comm., April 11, 2016).

In contrast with the earlier runs, the Summer 4_1 group has been abundant in recent years. This management unit is primarily impacted by troll fisheries in Southeast Alaska and Northern BC, in-river First Nations fisheries, and the Northern BC and Fraser River recreational fisheries (DFO 2011a). There is interest in increasing harvest of this stock if forecasts indicate that abundances are sufficient (Chuck Parken, Stock Assessment Biologist, DFO. July 28, 2015). Specific management objectives, in conjunction with biologically-based escapement goals, are currently being developed for this management unit (DFO 2015a).

Fraser Fall Chinook are the only management unit in the Fraser River that has pre-season forecasts and a biologically-based escapement goal. Forecasts are produced with sibling models and are used as inputs into DFO's coast-wide Chinook model for planning mixed-stock ocean fisheries. The Fall Chinook forecast is not updated in-season due to a lack of available information (DFO 2011a), although it is used to enact regulations when forecasted escapements fall below the escapement goal. Actions primarily affect in-river recreational or Chum fisheries (DFO 2015a; M. Maxwell, pers. comm., April 11, 2016)..

1.2. Genetic Stock Identification (GSI)

I utilize GSI data for Fraser Chinook caught in the Albion test fishery to develop catch indices for stock aggregates. For Chinook Salmon, coded wire tags (CWT's) have traditionally been used to identify stocks of origin in mixed stock fisheries (Beacham et al. 2008, Parken et al. 2008). However, genetic methods are increasingly being applied (Hess et al. 2014), as they have the combined benefits of high accuracy and precision, while being easy, quick, and cost effective once baselines are established (Beacham et al. 2004a, 2004b, 2014b, Parken et al. 2008, Flannery et al. 2010).

GSI methods are applied to numerous mixed-stock fisheries, and have proven effective in enabling managers to address the challenge of providing harvest opportunities whilst restricting impacts on stocks of concern (Beacham et al. 2004a, 2004b). To this end, GSI has been used to estimate migration timing (Beacham et al. 2014a, 2014b, Hess et al. 2014); migration pathways (Shaklee et al. 1999, Beacham et al. 2014a); relative contributions or presence of individual stocks in mixed-stock fisheries (Shaklee et al. 1999, Beacham et al. 2008); and in-season stock-specific abundances (Shaklee et al. 1999, Beacham et al. 2004b, Flannery et al. 2010, Hess et al. 2014).

In British Columbia, Alaska, and the Columbia River system, GSI is used as a management tool in combination with test or commercial fishery indices (Beacham et al. 2014b), providing information on where and when to fish in order to avoid or target specific stocks (Beacham et al. 2014b). However, integration of GSI methods into management systems has not been as widespread as would be expected based on its proven potential (Waples et al 2008; Satterthwaite et al 2015). In order to use GSI to correctly identify stocks, baselines must first be established to represent all populations present within the target fishery (Waples et al. 2008, Parken et al. 2008). Even then, the suitability of this method depends on the amount of genetic variation present in the populations being characterized (Shaklee et al. 1999, Waples et al. 2008).

GSI methods have previously been evaluated for Fraser Chinook by Beacham et al. (2003), and Parken et al (2008). Beacham et al. (2003) used a simulated sample, two years of commercial fishery data, and one year of test fishery data (Albion test fishery), to test the accuracy of the microsatellite variation method for estimating Chinook stock composition and individual stock IDs in the lower Fraser River. For individual assignments the mean error was 70% for individual populations, although this varied across populations, with Lower Fraser, and Lower and North Thompson populations having the highest accuracy. Individual assignment accuracy was 80% to the correct regions. Parken et al. (2008) used cross-validation to evaluate the accuracy of GSI methods for CWT-identified samples. Classification was 69% accurate to individual populations, and 92% to Fraser Chinook management units. Results from these analyses indicate that GSI-derived stock compositions are sufficiently accurate for application to management in mixed stock fisheries (Beacham et al. 2003a). Further studies suggest that GSI provides key information on stock specific abundances and can be used to develop stock-specific indices for Fraser Chinook (Parken et al. 2008, Hess et al. 2014).

My objective was to evaluate in-season forecasting models for each of the Fraser Chinook management units: Spring 4_2, Spring 5_2, Summer 5_2, Summer 4_1, and Fall. For this, I used GSI-analyzed Chinook catches and corresponding effort data from the Albion test fishery to develop management unit-specific cumulative CPUE indices for each week of available data. To account for potential differences in CPUE indices according to net type, I generated three indices, consisting of catch and effort data from the single panel net-type, multi-panel net-type, and combined net-types used in the Albion test fishery.

2. Methods

I used three model forms to relate CPUE indices to the estimated in-river returns of each Fraser Chinook management unit on a weekly basis: linear, exponential, and allometric. These functions were fit to the three sets of CPUE indices (single panel, multi-panel & combined) for each Fraser Chinook management unit using Bayesian methods to represent uncertainty in the estimates. I additionally produced composite forecasts, which combine the three model forms for each management unit and set of indices. I evaluated model fit and convergence using standard diagnostics (Dodds and Vicini 2004, Toft et al. 2007, Gelman et al. 2014). The predictive ability of each applicable model was assessed for individual management units, using a cross-validation analysis to identify models that perform best in terms of forecast accuracy. As part of this performance evaluation, I included the current in-season model for Spring and Summer 5_2 management units, to determine whether GSI-based models outperform the existing method.

2.1. Data

To develop the in-season forecasting models, I relied on three types of data: test fishery catch and effort, GSI assignments, and annual return estimates by management unit. Return estimates represent the Chinook abundances at the Fraser River mouth, after ocean fishery harvests. Stock compositions were assigned based on the most recent categorization by Fraser River Stock Assessment, DFO (C. Parken, Stock Assessment Biologist, DFO, pers. comm., May 19, 2016) (Table 2). Any stock for which either GSI or return data were not available was excluded from the analysis.

Albion test fishery catch and effort

Catch and effort data for CPUE indices were acquired from the Albion test fishery database through DFO. The Albion test fishery was established in 1980 to assess in-river relative abundances and migration timing of Fraser Chinook (Dempson et al. 1998). Albion is located near the up-river end of McMillan Island, approximately 50 km upstream of the Fraser River mouth (Dempson et al. 1998). The test fishery operates at this location daily from April 1st to mid-October, although the start date has varied recently (Chamberlain and Parken 2012). Two consecutive 30-minute drift net sets are made daily, timed to occur just prior to, and after, the daylight high tide (DFO 2011a). The duration of each set is affected by the velocity of the river, debris, and catch (Dempson et al. 1998), but the average daily fishing time (61.9 minutes) shows no trend over time (Dempson et al. 1998), and each set length is recorded, including the time taken to set and recover the net.

The fishery has been operated consistently since its initiation, experiencing few changes in terms of materials or methods (Dempson et al. 1998, Parken et al. 2008). The Chinook-directed test fishery operates annually until October 20th (DFO test fishery website), using a 200-fathom, 8-inch multifilament Chinook net, which has been the standard since 2004. Prior to 2004, the net was 150 fathoms. Since 1997, a multi-panel net has been fished on alternate days to fully represent the range of Fraser Chinook body sizes and to minimize the potential bias towards catching larger fish (Dempson et al. 1998, DFO 2006b). One exception to this pattern occurred in 2001, when the single panel net was not used until May 14th, and the multi-panel net was fished on every second day from April 1st onwards. The multi-panel net is a 200 fathom net comprised of panels ranging from 6 to 9 inch mesh, although prior to 2004 the net also included a five-inch panel. Additionally, from 2004 to 2007 after July 15th, a large multi-panel net, with panels ranging from 7 to 9 inch mesh, was fished. After August 31st, the Chinook-directed test fishery is operated on alternating days with the Chum-directed test fishery, and uses only the 8 inch net.

GSI Data

Tissue samples are collected from nearly every Chinook caught in the Albion test fishery as part of the standard biological sampling routine (Bailey et al. 2001). Samples have not been GSI analyzed for every year of the test fishery, as these analyses are costly. GSI results were available from DFO's Molecular Genetics Lab for the 2000, 2001, 2005, 2006, and 2008-2014 test fishery samples (A. Araujo, Aquatic Science Biologist, DFO, pers. comm., May 27, 2016), totalling 16,860 analyzed fish, and representing 75% of the total Albion catch in these years. However, the rate of analyses is not equal for each year (Table 3). Rates of sample analysis for years 2000, 2001, 2005, and post-August 31st 2008 (average 71% of samples analyzed), were lower than in more recent years (average 98% of samples analyzed). This creates bias in the catch estimates for these years. I therefore expanded catch estimates for the affected years by calculating the proportion of analyzed samples attributed to each management unit for each week and multiplying that proportion by the total sampled catch for that week. This expansion assumes that the analyzed samples are representative of the weekly catch at Albion.

GSI analyses produce two stock identification outputs: a catalogue of stock composition, which summarizes the proportion of each stock in the entire sample and includes an estimate of error; and individual stock IDs, which present the most likely stock IDs for each sampled fish in order of their associated marginal probability. Although stock proportions are more accurate than individual fish IDs, because more information is available at the mixture level (Beacham et al. 2003a), individual classifications were used to perform this analysis, because of the weekly time-scale. The highest probability individual stock assignments were rolled up into management unit catch estimates. Overall, IDs were associated with moderate to high assignment probabilities; less than 15% of samples had marginal probabilities that were 0.5 or less, while more than 50% had probabilities that were 0.8 or greater.

CPUE Indices

CPUE indices were derived using management unit-specific catch estimates from the GSI analysis, and total effort of the Albion test fishery. Effort was calculated in fathom-minutes per boat day, as the product of total daily fishing time and the length of the net fished (200 fathoms for most years, 150 fathoms for the single panel net in 2000 and 2001), according to the method outlined in Schubert et al. (1988).

$$Effort_d = \sum_{s=1}^{S} \left(soak\ time_{s,d} + \frac{1}{2} set\ time_{s,d} + \frac{1}{2} retrieval\ time_{s,d} \right) X\ \ (net\ length) \quad (1)$$

where *s* is the set number, *S* is the total number of daily sets fished, and *d* represents day. Catch-per-unit-effort indices were calculated as the ratio of the total weekly (*w*) catch for each management unit (*MU*) and the total weekly fishing effort.

$$CPUE_{MU,w} = \frac{\sum_{d=1}^{7} Catch_{MU,d}}{\sum_{d=1}^{7} Effort_d} \quad (2)$$

I developed CPUE indices on a weekly time-scale to line up with the current requirements of aggregated Spring and Summer 5_2 Chinook management, for which in-season forecasts are produced on a bi-weekly basis in the early summer (M. Maxwell, pers. comm., April 11, 2016). Weekly CPUE indices were summed from the start week to produce cumulative indices. Start weeks were standardized at statistical week 19, referring to the first week of May (Table 1), across all years to account for variation in the annual start date of the test fishery.

In addition to total CPUE indices, I developed indices specific to the two net types: single panel and multi-panel. I calculated these indices using the same method outlined above, separating catch and effort data by the net used for each day of fishing, and summing these estimates over weeks.

In-river Returns

Return data for Fraser Chinook management units were obtained from Fraser River Resource Management, DFO (M. Hawkshaw, Fisheries Assistant, DFO, Dec. 4, 2015). Annual returns are estimated for Fraser Chinook stocks using a backwards run-reconstruction model developed in 2007. The model uses escapements, fishery catches, and assumptions about run timing, movement rates and fishing patterns to reconstruct stock-specific harvest rates, catches, and in-river abundances (English et al. 2007). Due to the numerous model assumptions, return estimates are undoubtedly associated with error, although this error has not been quantified.

2.2. Forecasting Models

Three in-season forecast models forms were fit to each datasets: linear, exponential, and allometric. Composite forecasts were subsequently produced, combining forecasts from the three model forms. Models were selected to align with previous work on in-season forecasting for Fraser Chinook (Parken et al. 2008, Chamberlain and Parken 2012). I evaluated each model to identify those that best represented the relationship for each Fraser Chinook management unit.

The linear model takes the form

$$\hat{R}_{t,MU} = \alpha + \beta\, CPUE_{MU,w,t}, \tag{3}$$

where $\hat{R}_{t,MU}$ is the return estimate for year *t* by management unit (MU), and $CPUE_{MU.w,t}$ is the cumulative CPUE index up to week *w* in year *t* by management unit (MU). The linear model form implies that there is a minimum abundance at which the test fishery begins to catch samples, and above that value the catch rate is proportional to the total return (Flynn and Hilborn 2004). The linear model was fit under the assumption of normally distributed errors with the following likelihood function:

$$P\left(R_{t,MU}\middle|\alpha,\beta,\sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{\left(R_{t,MU}-\widehat{R_{t,MU}}\right)^2}{2\sigma^2}\right]; \tag{4}$$

and the likelihood of the return dataset defined as:

$$P\left(R_{1,\ldots,T,MU}\middle|\alpha,\beta,\sigma\right) = \prod_{t=1}^{T} P\left(R_{t,MU}\middle|\alpha,\beta,\sigma\right) \tag{5}$$

where $\hat{R}_{t,MU}$ is the estimated return for year *t* and management unit *MU* from equation 3, $R_{t,MU}$ is the observed return in year *t* from management unit *MU,* and *T* is the total number of years of return data in the dataset for each management unit.

The exponential model is defined as,

$$R_{t,MU} = e^{\alpha+\ \beta\ CPUE_{MU,w,t}} \quad . \tag{6}$$

This model form allows returns to increase exponentially in relation to cumulative CPUE, assuming that at higher return abundances the test fishery cumulative CPUE levels off. The exponential relationship is indicative of net saturation a high abundances, also known as hyperstability (Hilborn and Walters 1992). This relationship has been proven to occur in CPUE indices derived from commercial salmon fisheries (Hilborn and Walters 1992), and has also been shown in test fishery indices (Link and Peterman 1998).

Finally, the allometric model was defined in Chamberlain and Parken (2012) as

$$R_{t,MU} = \ \alpha CPUE_{MU,w,t}^{\beta} \ , \tag{7}$$

where there is no minimum run size implied before the test fishery begins to catch samples. Here the scaling parameter α represents the returns per cumulative index point at cumulative CPUE=1. The exponent, β, determines either the growth or decay of that sampling rate, where a value of 1 represents a straight line, values > 1 have increasing returns per cumulative CPUE, and values <1 have decreasing returns per cumulative CPUE. This model form can represent hyperstability, or its inverse, hyperdepletion, in the relationship between CPUE indices and return abundances (Hilborn and Walters

1992). Parken et al. (2008) found that this relationship better represented the variability in run size as a function of Albion test fishery indices at the population level than a linear model. Subsequently, this model form is currently used to forecast Fraser Spring and Summer 5_2 Chinook.

The exponential and allometric models were linearized and fit under the assumption of normally distributed errors on the log-scale, which gives the following likelihood:

$$P\left(R_{t,MU} \middle| \alpha, \beta, \sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{\left(\ln(R_{t,MU}) - \ln(\widehat{R_{t,MU}})\right)^2}{2\sigma^2}\right] \quad (8)$$

where $\hat{R}_{t,MU}$ is the estimated return for year *t* and management unit *MU* from equation 6 in the case of the exponential model, and equation 7 in the case of the allometric model. $R_{t,MU}$ is the observed return in year *t* from management unit *MU.*

All models were fit using Bayesian methods via R Statistical Software, version 3.2.3 (packages ‘R2OpenBUGs’, ‘coda’,& ‘car’) (available at www.r-project.org) and OpenBUGs (Bayesian Inference Using Gibbs Sampling), version 3.2.2 (http://www.openbugs.net). Vague priors were used for all parameters [α~N(0, 1.0*10^{-11}); β~N(0, 1.0*10^{-11}); τ ~G(0.01. 0.01)]. Models were run each with two Monte-Carlo Markov-Chains (MCMC), and were monitored for convergence before the initial samples were removed as ‘burn-ins’, and 8,000 samples were subsequently taken from the posterior parameter estimates, storing every fourth value to remove autocorrelation in the samples and improve mixing of the chains (Toft et al. 2007). Weeks with fewer than five annual data points at the management unit level were not included in the evaluation.

Composite forecasts were subsequently generated by combining the posterior forecast distributions of the three model types, for each management unit and CPUE dataset, and sampling 2,000 estimates from the combined posterior. Forecast averaging is a common method used to reduce forecasting errors associated with systematic bias, data errors, and unsatisfied model assumptions (Armstrong 2001). Though they have been contested by some researchers, this approach allows forecasters to explore alternative approaches that may improve accuracy (Armstrong 2001), and they have performed well in a fisheries context (Haeseker et al. 2008).

Convergence Diagnostics

Convergence refers to the process through which MCMC samplers reach their target distribution. Convergence of MCMC chains cannot explicitly be proven; however, a lack of convergence can be identified using a number of diagnostics (Toft et al. 2007). I examined trace plots, Gelman-Rubin diagnostics, and Geweke values to determine when MCMC chains approximated convergence for each model. Trace plots show the MCMC pathways as chains move from their initial values towards the 'true' distribution (Dodds and Vicini 2004). In order to properly reach convergence, trace plots must show that the chains mixed properly, and explored the parameter space in a stable manner (Dodds and Vicini 2004). I examined these plots visually to determine whether the chains showed evidence of improper mixing and instability. The Gelman-Rubin diagnostic, a quantitative indicator of stationarity, signifies that the burn-in period is complete once chains have stabilized. The Gelman-Rubin diagnostic estimates a 'shrink factor', which represents the factor by which the scale parameter may shrink if sampling were continued indefinitely. The scale parameter compares between chain variance to within chain variance. The shrink factor approaches 1 when the chains are no longer influenced by their initial values and have properly explored the parameter space (Cowles and Carlin 1996). I set the critical value of the Gelman-Rubin diagnostic to 1.1, to indicate whether the chains had reached convergence. I also examined another measure of stationarity, the Geweke diagnostic, which compares initial portions of the Markov chains to the end portions using z-scores. Scores that fall outside the critical values (-2.5 to 2.5) are considered aa significant indications of non-stationarity (Dodds and Vicini 2004). Lastly, I inspected autocorrelation in the posterior samples to ensure that the thinning interval were sufficient to overcome any autocorrelation in the chains, by comparing the lag-5 term to the critical value for each analysis.

2.3. Cross-Validation

I used cross-validation to identify models that produce the best forecasts for each management unit, based on the selected performance measures. Cross-validation is the appropriate method for evaluating forecasting models, because errors are calculated using data that are not employed in model fit (Hyndman and Athanasopoulos 2013). Cross-validation encompasses a variety of methods applied in evaluating the predictive ability of models in comparison to one another. Data is split into two samples, one of which is used to fit the model, and the other is used to test predictions. Due to the limited number of years of data available for this analysis, I applied a leave-one-out cross-validation analysis to evaluate models for in-season Fraser Chinook forecasts. In accordance with this method, models were fit to datasets excluding one annual data point at a time. Each fit was used to forecast values for the excluded year. Forecasts could then be compared to observed values to estimate error in the model predictions.

Error was summarized according to a set of performance measures that quantify the accuracy and bias of the predicted estimates. I chose to apply three performance measures to estimate error in the in-season model forecasts:

$$\text{mean percent error (MPE)} = \frac{1}{n}\sum_{t=1}^{n}\frac{\widehat{R_{t,MU}}-R_{t,MU}}{R_{t,MU}} * 100\ , \tag{9}$$

$$\text{mean absolute percent error (MAPE)} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\widehat{R_{t,MU}}-R_{t,MU}}{R_{t,MU}}\right| * 100\ \ , \tag{10}$$

$$\text{and root mean squared error (RMSE)} = \sqrt{\frac{\sum_{t=1}^{n}\left(\widehat{R_{t,MU}}-R_{t,MU}\right)^{2}}{n}}\ , \tag{11}$$

where n is the number of years of data, $R_{t,MU}$ is the observed return from a management unit (MU) for year t, $\hat{R}_{t,MU}$ is the median predicted return to the management unit (MU) for year t from the fitted model, and n is the number of samples used to fit the model.

Mean percent error (MPE) reflects systematic biases in the predicted values, scaling the magnitude of the error by the true return so metrics can be compared between analyses (Walther and Moore 2005, Haeseker et al. 2008). Positive values of MPE indicate that the model consistently over-forecasts, while negative values imply under-forecasting. Alternatively, the mean absolute percent error (MAPE) and root mean squared error (RMSE) performance measures ignore the direction of biases to measure the overall accuracy of model predictions. I included two measures of accuracy, as they reflect different aspects of the data. The MAPE reflects central tendency, measuring the magnitude of distance between predicted and observed values, scaled according to the true return. The RMSE is calculated based on the squared error, therefore it is heavily affected by large deviations and reflects the presence of outliers in model fit (Walther and Moore 2005, Willmott and Matsuura 2005). Models with large outliers will, therefore, perform more poorly on the RMSE metric than models that minimise outliers.

Forecasts from each model were scored according to the set of performance measures. For comparison, the currently-used in-season methods for Spring and Summer 5_2 Chinook were also evaluated according to the cross-validation process and scored across performance measures. These methods use an allometric model and total cumulative CPUE from the single panel net to predict the combined returns of Spring and Summer 5_2 Chinook. I fit this model to corresponding data for the same years evaluated in this analysis, and calculated performance measures over those years. Additionally, to equally compare GSI-based methods to the current in-season model for aggregated Spring and Summer 5_2 Chinook, I summed median GSI-based forecasts of Spring and Summer 5_2 Chinook from the allometric model applied to single panel data, and calculated performance measures for these forecasts against summed Spring and Summer 5_2 returns.

Assessment of Net Type

I used values of the MPE and MAPE performance measures to visually examine the influence of net type on forecasting ability. To simplify further analyses, I determined which dataset to present for each management unit, based on relative model performance using each dataset. MPE and MAPE are scaled according to true returns, and therefore can be intuitively compared across analyses. I removed data after statistical week 35 from this assessment, because the multi-panel net is only fished until week 35 (August 31st), Consequently, the Fall Chinook management unit was excluded from the net type analysis, as Fall Chinook do not consistently appear in the CPUE data until statistical week 34 (late August). CPUE indices for Fall Chinook were, therefore, restricted to single panel data only, to maintain consistency across statistical weeks.

2.4. Model Fit Diagnostics

The retrospective analysis evaluated models based only on their median forecasts. I, therefore, further evaluated model performance using a series of posterior predictive checks. These model fit diagnostics were not used to select models with the best fit. Posterior model checks are intended to detect systematic divergences between the model and the data (Gelman et al. 2000), and are therefore used to identify ill-fitting models. Posterior predictive plots have been proposed as a Bayesian alternative to classical model testing methods (Gelman et al. 2000). These checks involve estimating replicated datasets from simulations of the fitted model (i.e. using draws from the posterior distributions of the model parameters), which are compared to the observed values. If replicated distributions align with observed values across the dataset, model fit is considered appropriate, whereas systematic differences may be an indication of a poor model (Gelman et al. 2014). I generated posterior predictive distributions of annual returns across the three model forms fit using Bayesian methods (linear, exponential, and allometric). I then compared observed returns to the 95% highest posterior density (HPD) region for replicated data, and calculated the percentage of years that fell outside this range for each weekly model fit (Hyun et al. 2005, Holt et al. 2009).

3. Results

3.1. Model Convergence

All model scenarios satisfied the evaluation criteria for convergence within the specified number of MCMC iterations, and, therefore, no burn-in periods were increased. Trace plots all indicated that sampling chains mixed well and explored the parameter space. Gelman-Rubin diagnostics fell at, or very close to 1.0, with a maximum value of 1.01 across all modeled scenarios, and Geweke values fell between -2.5 and 2.5 for all parameters. Autocorrelation within the chains did not exceed critical values for lags up to and including lag-5, indicating that the thinning interval of four was sufficient to account for any autocorrelation within the chains

3.2. Cross-Validation and Model Fit

To compare models across analyses, performance measures are generally calculated using the same years of data. CPUE indices are not available in all years for analysis weeks that fall early in the migration of Fraser Chinook management units. This required removing some analysis weeks from the cross-validation procedure for each management unit, due to the discrepancy in sample sizes. However, since timing is an important criterion for in-season forecasting, and it is of interest to evaluate models for early analysis weeks, I allowed a buffer of two missing years in each evaluation.

Effects of Net Type

Comparison plots of MPE and MAPE indicate that net type has no consistent effect on the performance of models for the Spring $4_{2,}$ Summer 5_2 and Summer 4_1 management units. Overall, values for these MUs fell on or close to the 1:1 line, with the exception of between one and four values per plot, representing the poor performing exponential model, and in the case of Summer 4_1's also the linear model, in the first few analysis weeks (Spring 4_2: weeks 24-26; Summer 5_2: weeks 26 & 27; Summer 4_1 weeks 28 & 29) (Figure 3-Figure 6). Without these points, associations between performance measures, quantified using Pearson's correlation coefficient, fell at or above r=0.85. Since deviations are limited to only a few model-week scenarios, none of which perform well, compared to other scenarios, I have presented the combined net data for the Spring 4_2, Summer 5_2, and Summer 4_1 management units,

Performance measures for the Spring 5_2 models indicate that higher accuracy and lower bias can be achieved using only single panel net data. For this management unit, performance measures calculated from models fit to single panel-only data have consistently better values compared to analyses using combined data (Spring 5_2 MPE r=0.71; MAPE r=0.64) (Figure 3-Figure 6). This is due to single panel-only data producing larger CPUE indices than combined data, and indicates that the single panel net catches more Spring 5_2 Chinook than the multi-panel net, given the same effort. Due to the superior performance of models using the single panel data for this management unit, single panel-only CPUE indices are presented for Spring 5_2 Chinook.

Performance Measure In-season Trends

Performance measures for all models generally improve across analysis weeks, reaching a peak then levelling off or declining. Timing of peak performance varies among management units, as expected due to differences in run-timing past the Albion test fishery (Figure 1). All models tend to over-forecast returns due to large positive errors caused by one year of data, for which CPUE indices are very large and returns are average (Figure 7-Figure 11). Accuracy measures MAPE and RMSE reflect very similar patterns across analysis weeks. Though for poor performing models, RMSE values are much larger relative to other models than the MAPE, implying that these are affected by outlying values.

In general, the allometric model performs well according to the MPE, MAPE and RMSE performance measures across weeks and management units. This model clearly outperforms the others in the majority of analysis weeks for all management units except Spring 4_2, where the exponential model is superior after week 28. Although the allometric model performs best in the first few analysis weeks for Spring 4_2 Chinook (Figure 7). In the earliest weeks of analysis for all management units, including Spring 4_2, though except Fall, the exponential model has the poorest predictive ability. The allometric model only performs worst in three specific cases, for the Spring 4_2 management group after analysis week 28 (MAPE and RMSE), for Fall Chinook after week 40 (MAPE and RMSE), and for Spring 5_2 Chinook in week 20 (MAPE only). These trends suggest that early in the fishing season the allometric model is the best choice to represent the relationship between cumulative CPUE and returns across management units, while use of the exponential model will result in the largest forecasting errors.

Model Performance for Individual Management Units

Since forecasts produced by the current aggregated Spring and Summer 5_2 Chinook forecasting method are used to update management actions in mid-June (week 24), I used performance of this method in week 24 as the standard against which GSI-based methods were compared (MPE=5%, MAPE=20%, rounded from 18%) (Figure 12). I also used the timing of current aggregated Spring and Summer 5_2 forecast availability (week 24) in relation to average median migration timing of Spring 5_2 Chinook (week 26/27) as a guideline to assess the availability of forecasts for other management units. I deemed forecasts useful if they fell more than 2 weeks prior to the median migration timing of respective management units, based on timing derived from Albion test fishery catch data. Timing guidelines were as follows: Spring 4_2-week 28; Spring 5_2-week 24; Summer 5_2-week 29; Summer 4_1-week 32; Fall-week 36.

Spring 4_2 Chinook

Data for the Spring 4_2 management unit were available for weeks 23 (early June) through 42 (mid-October), though no Spring 4_2 Chinook are present in the catch data for 2011. Forecasts of Spring 4_2, Chinook have the most relative error of all management units in terms of both bias (minimum MPE=20%: exponential model, week 28) and overall accuracy (minimum MAPE=50%: allometric model, week 23; minimum RMSE=6121: allometric model, week 26). Although no model performs well for this management unit in comparison to the current model for Spring and Summer 5_2 Chinook (Figure 12), those that perform best in relative terms, do so in the earliest analysis weeks available for this management unit (Figure 13), falling well before the Spring 4_2 timing guideline (week 28). Forecasts for Spring 4_2 Chinook perform best in early and mid/late June (weeks 23 & 25-26) and have absolute errors of ~50% (Table 5; Figure 7; Figure 13). Performance declines across all models for weeks 30 to 42.

Spring 5_2 Chinook

The best performing GSI-based models for Spring 5_2 Chinook, produce forecasts with MAPE's of 17-20%, and less than 5% average bias, outperforming the current model standard (Figure 12; Figure 14). For Spring 5_2 Chinook, models that perform well fall in early analysis weeks, prior to the timing guideline for the management group (week 24). The best performing model on average across metrics is the allometric model in week 21 (MPE=3%, MAPE=18%, RMSE=6481), followed by the same model in week 20. The allometric model in week 20 performs best on the MPE (0.4%), while the linear model in week 20 performs best on the MAPE (16%) and RMSE (RMSE=5204) performance measures. Average absolute error remains close to 20% for the allometric model throughout the analyses, while bias (MPE) remains under 5% (Table 6; Figure 8; Figure 14). Forecasts for Spring 5_2 Chinook can therefore be produced in any analysis week using the allometric model, with similar forecasting performance to the current standard.

Summer 5_2 Chinook

The case is similar for Summer 5_2 Chinook. Although average absolute error is smallest after week 36 (MAPE=14%), forecasts as early as week 25 do not perform much worse (max. MAPE=21%). Accurate forecasts (MAPE=18%) can be produced prior to the availability guideline for Summer 5_2 Chinook (week 29), by mid-to-late June, (week 26) with little bias (MPE=6%), though this falls slightly above the bias standard from the current model (Table 7; Figure 9; Figure 12; Figure 15). Forecasts that perform well on both the MAPE and MPE metrics can be produced in any of the evaluated analysis weeks for Summer 5_2 Chinook, using the allometric model (Figure 15). Good performing forecasts may also be produced by the composite model after week 29 (Figure 9).

Summer 4_1 Chinook

The best forecasts for Summer 4_1 Chinook perform poorly compared to the current standard, with 38% error and 12% bias (Figure 12), and are produced in late August (week 35) (Figure 16). Performance of Summer 4_1 forecasts is generally better in later analysis weeks, falling after the availability guideline for this management unit (week 32) (Figure 10; Table 8). However, relative to the best performing models for this management unit, earlier forecasts do not perform much worse, particularly using the allometric model, for which MPE ranges from 11% to 13%, and MAPE from 38% to 43% across analysis weeks. In the availability guideline week for Summer 4_1 Chinook (week 32), forecasts produced by the allometric model have 12% bias and 41% accuracy.

Fall Chinook

Forecasts of Fall Chinook show the least consistency across performance measures, and the largest apparent trade-offs between accuracy, bias, and forecast availability (Table 9; Figure 11; Figure 17). More accurate forecasts of Fall Chinook are associated with larger bias, and are produced by models in later weeks, though no forecasts perform well compared to the current model standard (Figure 12; Figure 17). The allometric model shows the least bias for most analysis weeks, though the composite and exponential models perform better in week 35 (Figure 11; Table 9). The best values of both the MAPE and RMSE occur in week 42, produced by the exponential and linear models, respectively. Despite shifts in relative value, bias remains small for most models and weeks using the allometric or exponential models (<5%), and the overall best performing forecasts can be produced for this management unit in early September (week 36), falling on the availability guideline (week 36), with 31% error (Figure 17).

Comparison of Current to GSI-based Methods for Combined Spring and Summer 5_2 Chinook

Performance measures indicate that the current method of forecasting combined Spring and Summer 5_2 Chinook, using total CPUE indices, performs best in analysis weeks 20 and 21, with less than 1% bias, with an average error of ~10% (Figure 18). Unfortunately, GSI-based methods for forecasting aggregated Spring and Summer 5_2 Chinook cannot be evaluated for these weeks, as forecasts of Summer 5_2 Chinook cannot be generated until statistical week 22 (late May). Also, although forecasts from the early season (statistical weeks 22-25) are included for Summer 5_2 Chinook, note that until statistical week 25, CPUE indices used by the GSI model are missing at least two years of data.

Although GSI-based forecasts of Spring 5_2 and Summer 5_2 Chinook perform the best of all the stock groups, with the greatest accuracy and least amount of bias, aggregated forecasts using GSI methods do not perform better than those produced by current in-season methods in early analysis weeks (weeks 22/23 – late May/early June) (Figure 18Figure 18. Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) of the current in-season Spring and Summer 5_2 forecast model (pink bars), and the allometric model applied to single panel CPUE indices for the Spring 5_2 and Summer 5_2 management units combined (blue bars). Statistical weeks of analysis are indicated on the x-axis.). Early season forecasts (statistical weeks 22 and 23), using GSI-based single panel indices and the allometric model, have relatively large bias, and an average error of 15% (Figure 18). However, bias in the GSI methods improves substantially at week 24, to approximately 1%.

Therefore, GSI-based forecasts of aggregated Spring and Summer 5_2 returns perform better than the current method in week 24 (second week of June) (MAPE reduced from 18% to 15%; MPE from 5% to -0.1%), the week in which forecasts are required for in-season management applications. GSI-based forecasts also perform better from late June (week 27) onwards (except week 29). During July, GSI-based methods reduce the MAPE and MPE of forecasts by 1-2%, which increases to 6-7% in the MAPE reduction in August (21% to 15%) (Figure 18), as total CPUE indices respond to rising abundances of Summer 4_1 Chinook in the lower Fraser River, and performance of the current method is degraded.

Apart from the initial two analysis weeks (20 and 21), for which only one model is evaluated, the best MAPE and MPE are associated with the GSI-based model in weeks 27 and 25, at 11% and 0.2%, repsctively. The RMSE performance measure shows a more consistent trend in model performance, with the current method outperforming the GSI indices until statistical week 26, at which point roles reverse (Figure 18).

3.3. Assessment of Model Fit

In addition to performance measures, I examined posterior distributions of model-simulated returns, and compared these to observed values as an indication of model fit. The frequency with which the true returns fall within the 95% highest posterior density region (HPD) of the replicated data (coverage frequency) is 100% for all weeks across models and management units with the exception of Spring 4_2 Chinook (Table 4). For this management unit, the 2009 annual return (10% of the data set) falls outside the 95% HPD region of replicated values generated by the three fitted models, though the number of weeks for which this occurs varies. For all models the week 29 analysis produces a 90% coverage frequency. The exponential model also produces this result in weeks 38 and 40, while the allometric model shows 90% coverage in weeks 27, 28, 31, 34, and 41 in addition to week 29.

4. Discussion

Accuracy is an important component of forecasting, as error can lead to missed escapement targets, impacting conservation objectives or fishing opportunities (Noakes 1989, Zheng and Mathisen 1998). Even small improvements in the accuracy of forecasts can potentially benefit stakeholders in attaining objectives (Noakes 1989). However, because in-season methods become more accurate as the fishing season progresses (Fried and Hilborn 1988, Catalano and Jones 2014), improvements in forecasting accuracy can come at the cost of delayed availability, which can also impact their utility (Pearse 1982, Woodey 1987, Claytor 1996). I evaluated whether accurate and timely forecasts could be produced for Fraser Chinook management units with the addition of GSI data to CPUE indices. The GSI-based models produced accurate and timely forecasts for two of the five management units, and less accurate forecasts for the remaining groups, though these forecasts are still potentially useful to management.

Although trade-offs are apparent in the relationships between accuracy, bias, and analysis week for Fraser Chinook, in many cases forecasts perform well early in the fishing season. I found that GSI-derived forecasts for Spring 5_2, and Summer 5_2 Chinook have similar predictive errors to forecasts that are currently used for aggregated Spring and Summer 5_2 Chinook (MPE<5%; MAPE<20%), and are available more than two weeks prior to their respective median migration dates at Albion. Conversely, forecasts of Spring 4_2, Summer 4_1, and Fall Chinook did not perform well in terms of accuracy and bias measures in relation to the current standard, producing forecasts with 20-50% absolute accuracy and 0-25% bias.

Developing indices of abundance from fisheries data that reflect patterns in true abundances is a central problem for stock assessment programs (Hilborn & Walters 1992). Despite standardization, test fishery CPUE indices are subject to external variability that does not stem from fluctuations in returning abundances or run timing. This variability presents challenges for in-season management, creating error and uncertainty in forecasts (Marshall et al. 1987, Flynn and Hilborn 2004, Hyun et al. 2005, Catalano and Jones 2014). Indices may be affected by factors such as gear saturation, size selectivity, migration timing, environmental factors, salmon behaviour, variation in stock-age compositions, and non-representative sampling (Marshall et al. 1987, Hilborn and Walters 1992, Dempson et al. 1998, Chamberlain and Parken 2012, Beacham et al. 2014b). I removed one major source of variability, specifically, that created by overlapping run timing between stock groups, to develop management unit-specific indices for Fraser Chinook. However, additional sources of variability remain within the indices, and are reflected in forecasting predictive errors.

For all management units except Spring 4_2, the allometric model produced the least amount of error in forecasts. This corroborates the findings of Parken et al. (2008), who determined that the allometric model provided a better fit to population-specific Fraser Chinook CPUE indices and returns than a linear model. Similar results have also been found for Southeastern Alaska Pink Salmon, where a comparable non-linear model better represented the relationship between run size and CPUE (Zheng and Mathisen 1998). The exponential and allometric models produce more realistic forecasts for Fraser Chinook management units than the linear model, because lower values are bounded by zero, and errors are multiplicative. In all cases of the fitted allometric models, posterior probability distributions of the parameter β fell below 1 across management groups and weeks. This represents declining relative returns per cumulative CPUE index point as both increase, also known as hyperdepletion (Hilborn and Walters 1992). Hyperdepletion may indicate that components of the management units are differentially vulnerable to the gear used the test fishery. Size selectivity is a well-known cause of patterns of hyperdepletion in CPUE indices (Hilborn and Walters 1992). In the case of the Albion test fishery, the multi-panel net is used on alternating fishing days to reduce size selectivity because the single panel net has been shown to bias catch towards larger body sizes (Dempson et al. 1998, DFO 2006a).

Models developed in this analysis are limited by the accuracy of the data and assumptions they are built on. Here there are many uncertainties that are not explicitly captured by the forecast distributions. First, historical return data are estimates derived from Chinook run reconstruction (English et al. 2007). The reconstruction model makes assumptions about the run timing and movement rates of stocks from the mouth of the Fraser River to their natal spawning streams, the vulnerability of stocks to the gear types, and the daily pattern of fisheries (English et al. 2007). Additionally, it assumes that escapement and catch estimates are accurate and complete (English et al. 2007). However, escapements, the building block of return estimates, are derived from visual surveys, mark-recapture assessments, electronic counters, and coded-wire tag analyses (DFO 2011a), each of which is associated with its own set of errors and assumptions. Due to the lack of error quantification in the catch estimates, error is not propagated through to the return estimates. Second, test fishery indices are assumed to be without error, though this is unlikely, and is probably most heavily impacted by error in the GSI stock assignments. Parken et al. (2008) quantified individual GSI assignments as 92% accurate to Fraser Chinook management units, though this error is not propagated into the CPUE indices. Unquantified errors in both the CPUE and return estimates are not reflected in the uncertainty of the forecast distributions, therefore the amount of uncertainty in the forecasts is underrepresented. If this error were quantified, it could affect the overall performance of model forecasts. Third, data used for this analysis are limited to eleven years. Therefore they do not represent the range of conditions likely experienced, and predictions are restricted by those outcomes represented in the data.

I recommend that additional years of data be GSI analyzed, particularly those exhibiting large total CPUE values, where data are currently limited. Additional data would also benefit management units for which available data poorly represent the range of returns observed. This is particularly true for those management units that have a lot of relative variability in their run sizes, and consequently a lot for error in their forecasts (Spring 4_2, Summer 4_1, and Fall). The addition of data to better represent the range of returns, particularly for Spring 4_2 and Summer 4_1 Chinook, will likely inform the regression relationships for these management units, improving forecasting ability and better representing forecast uncertainty.

Additional GSI data will also likely improve the performance of the GSI-based methods earlier in the fishing season, where sample sizes are limited in comparison to the current method. Aggregated forecasts of Spring and Summer 5_2 Chinook produced using GSI methods did not perform better than the current in-season method prior to week 24. Poor relative performance of the GSI-based method in these early analysis weeks is most likely caused by small sample sizes in Summer 5_2 CPUE indices up to week 24, which creates larger standard errors in model fit for these weeks. Although GSI-based methods performed better specifically in week 24, improvements in performance due to the use of GSI indices was inconsistent until week 30, falling after in-season information is required to manage Spring and Summer 5_2 Chinook as an aggregate.

Variability in total CPUE indices affects the forecasting accuracy of the current in-season method, due to fluctuating returns of co-migrating management units. Hence, poorer performance of the current method in relation to GSI-based methods after week 30 is likely the result of increasing abundances of Summer 4_1 Chinook entering the lower Fraser River throughout late July and August (Chamberlain and Parken 2012). The effect of Summer 4_1 Chinook on the total CPUE indices reduces the ability of the current method to accurately forecast aggregated Spring and Summer 5_2 returns. Conversely, the notable performance of the current method in early weeks of the fishing season, as early as mid-May (weeks 20 and 21), suggests that return estimates are heavily influenced by catch rates of Spring 4_2 and Spring 5_2 Chinook in these weeks. Based on the GSI data, 80% of catch at Albion in weeks 20 and 21 is attributed to Spring 5_2 Chinook, while 15% is Spring 4_2 Chinook. Summer 5_2 Chinook represent less than 10% of Albion catch indices up to early-June (week 23). The accuracy of forecasts for the aggregate therefore depends on co-variation between the Spring 5_2, Summer 5_2, and to a lesser extent the Spring 4_2 management group. Spring 4_2, Spring 5_2, and Summer 5_2 Chinook have displayed similar trends in returning abundances since the mid-1990's, the exceptions being 2009 and 2012. Whether this will continue into the future is unknown. If returning abundances of Spring 4_2, Spring 5_2 and Summer 5_2 Chinook become dissociated in the future, accuracy of the current in-season method may be compromised, at which point GSI-based methods will become necessary for in-season prediction.

4.1. Management Implications

Fishery harvest strategies typically aim to meet biologically-based escapement goals by adjusting target harvest rates in response to annual variation in return abundances (Link and Peterman 1998). Return forecasts inform managers about expected returns and, therefore help to align harvest plans with those abundances (Woodey 1987). Within a fishing season, managers evaluate regulations in light of in-season abundance estimates, and make decisions regarding future allocations (Henderson et al. 1987, Fried and Hilborn 1988). This process can occur on daily, weekly, or monthly time-scales, as well as only once during the fishing season (Minard and Meacham 1987, Woodey 1987, Fried and Hilborn 1988, Hyun et al. 2005). The framework for updating regulations can impact the success of in-season management depending on the objectives. When a single forecast is used in-season to update allocations, the timing of that update is critical to success (Claytor 1996).

For Fraser Chinook, in-season management is largely centered on achieving escapement objectives for the Spring and Summer 5_2 stock aggregates, due to concerns about their status as well as a lack of information on other stocks (DFO 2011a). Pre-season forecasts are currently available only for the Fall management unit, and are not updated in-season (DFO 2011a). In-season forecasts are produced only for aggregated Spring and Summer 5_2 Chinook and are used to make one in-season update regarding allocation. This process employs the previously-described management zone system, as triggered by in-season Spring and Summer 5_2 aggregate forecasts. No quantitative estimates of abundance are available for Spring 4_2 or Summer 4_1 Chinook.

Although forecasts for all management groups did not meet the benchmarks set by the current in-season forecasting method for aggregated Spring and Summer 5_2

Chinook, these forecasts may still be informative. Zheng and Mathesin (1998) present in-season forecasts for Southeastern Alaska Pink Salmon that range in MAPE from 10% to 46%. These forecasts are an improvement upon pre-season forecasts for SEAK Pink Salmon, which have exceeded 200% in terms of relative error over the course of their use (Zheng and Mathisen 1998). Hyun et al. (2012) incorporated in-season methods to update pre-season forecasts for Pacific Fall Chinook and found that integrated forecasts performed better than preseason forecasts, reducing the range of MAPE across stocks from 22-43% to 15-36%. Forecasts for four of the five Fraser Chinook management units (excluding the Spring 4_2) performed better than forecasts used in these two management systems, and therefore should not be completely discounted based on their performance relative to the current method.

In-season forecasts for all Fraser Chinook management units would allow managers to adjust harvests of individual management units based on their predicted abundances (Zheng and Mathisen 1998). Adjusting harvest allocations in-season, based on in-season forecasts, helps managers attain management objectives, reducing the occurrence of over-harvest and under-harvest, and increasing harvests overall (Claytor 1996). This may be particularly useful in the case of the Summer 4_1 management unit, where potential harvesting opportunities are available, though the ability to formally plan for them is constrained by the lack of run size predictions (DFO 2015a).

The Summer 4_1 management unit is abundant enough in many years to support directed harvest, provided that harvesting activity does not adversely impact stocks of concern (DFO 2015a). However, regulations imposed to protect conservation concerns within the Fraser River dominate in-river management during the migration of Summer 4_1 Chinook. In the early summer, regulations are in place to protect Spring 4_2, Spring 5_2, and Summer 5_2 Chinook, to various degrees, depending on their in-season estimates (DFO 2015a). From mid-to-late summer through to Fall, fisheries within the Fraser River are managed according to objectives for Sockeye, and later, conservation concerns for Interior Fraser Coho and wild Steelhead (DFO 2011a).

Management constraints in mixed stock areas can result in larger escapements to terminal areas than are required to attain spawning goals (DFO 2012). This can also be the result of uncertain or inaccurate return estimates, when realized run sizes are larger than anticipated (DFO 2013). These factors create the opportunity for terminal fisheries (DFO 2012). Locating fisheries in terminal areas, close to spawning grounds where fewer stocks intermingle, rather than in mixed-stock marine areas, reduces mortality of non-target species or stocks (Plate et al. 2009). This allows managers to manage stocks according to population-specific harvest rates (Minard and Meacham 1987, Su and Adkison 2002). Such terminal fisheries are often associated with hatchery programs, as a method of creating fishing opportunities while directing harvest towards hatchery fish without impacting wild stocks (Kostow 2009).

For Fraser Summer 4_1 Chinook, realized escapements are affected by both in-river management constraints and uncertainty in run sizes, due to the lack of return forecasts for this management unit. Small-scale terminal commercial fisheries have targeted Summer 4_1 Chinook in Kamloops and Little Shuswap Lakes, located in the BC Interior near spawning areas, since 2009 (DFO 2013). However, currently the allowable catch in these fisheries is determined as a percentage of the annual commercial total allowable catch (TAC) transferred from unallocated licenses, primarily in Northern BC troll fisheries (DFO 2011a). Harvest rates are therefore not related to estimated returns of Summer 4_1 Chinook. Total allowable catch in the commercial troll fisheries is based on aggregated abundance forecasts for mixed stock ocean fisheries produced by the Chinook Technical Committee (CTC 2015b, DFO 2015a). The percentage of this TAC allocated to terminal commercial fisheries is determined prior to the fishing season (DFO 2013, 2015a).

In-season information on the returning Summer 4_1 run size would allow managers to refine target harvests of Summer 4_1 Chinook in terminal fisheries. Terminal harvest rates could be tailored to returns, and harvesting opportunities would not risk being under-utilized in these areas. Having more accurate and timely information to better manage terminal fisheries is beneficial both in terms of potentially increasing harvest, and reducing impacts on non-target stocks and species.

4.2. Future Research

The benefits of GSI-based forecasts for Fraser Chinook should be evaluated in a simulation analysis. Simulation can be used to assess the value of information or strategies within a management system in quantitative terms, such as differences in catch (Link and Peterman 1998, Catalano and Jones 2014), value of harvests (Link and Peterman 1998, Su and Adkison 2002), and probability of meeting escapement goals (Su and Adkison 2002, Catalano and Jones 2014). Simulation methods allow uncertainties within the system to be explicitly accounted for, such as those associated with population dynamics, forecasting, dynamics of harvesters, and data collection (Link and Peterman 1998, Su and Adkison 2002, Catalano and Jones 2014). Therefore, such studies are useful for objectively evaluating the benefits of management strategies in light of uncertainties within the system (Catalano and Jones 2014).

For Fraser Chinook, simulation analysis could be used to evaluate in-season management, while taking into account uncertainties in CPUE data, in-season forecasts, return estimates, and harvest implementation. In such, the timing of in-season decisions are evaluated in light of the accuracy of forecasts and uncertainties in the data, to determine if the additional costs of in-season GSI analysis are worth the potential gains, primarily in terms of harvests. Though GSI analysis is cheaper than previous methods of stock identification (Beacham et al. 2014b), analyzing samples of Chinook from the Albion test fishery in-season would require the allocation of annual resources that are currently not in place. If an annual framework for more precise in-season management of Fraser Chinook is implemented, an assessment of its benefits will be necessary in light of these costs.

Error associated with in-season forecasts of Fraser Chinook could be reduced with better representation of run timing, either through additional data, or methods such as including environmental variables in the models (Flynn and Hilborn 2004), or the using time-density models. In-season forecasting methods for Fraser Chum and Sockeye characterize in-season data using time-density models, which represent the pattern in CPUE indices over the fishing season as normal distributions (Gazey and Palermo 2000). The time density model explicitly describes run timing, therefore deviations in catch indices that are due to shifts in run timing rather than run size can be identified (Springborn et al. 1998).

Alternatively, pre-season information on return abundances could be incorporated, where available, into in-season forecasts. For Fall Chinook, pre-season forecasts may be combined with in-season estimates through informal or formal techniques, such as model weighting or Bayesian approaches (Walters and Buckingham 1975, Sprout and Kadowaki 1987, Fried and Hilborn 1988, Zheng and Mathisen 1998, Gazey and Palermo 2000, Hyun et al. 2005, Catalano and Jones 2014). Although combined estiamtes do not necessarily outperform independent forecasts in all cases, Fried and Hilborn (1988) found that estimates combined using Bayesian methods never performed worst, and they provided a convenient method of aggregating information from multiple sources.

Management of fisheries can be complex, due to the paired objectives of conserving stocks and species of concern while providing opportunities to harvest (Beacham et al. 2008, 2014a). In mixed stock scenarios, detailed information is required to ensure that objectives are met (Marshall et al. 1987, Beacham et al. 2004a). In this paper I evaluated whether GSI-based forecasting models for Fraser Chinook management units could help fisheries managers improve in-season harvest management. The GSI-based models produced timely and accurate forecasts for two of the five management units when compared to current Fraser Chinook forecasting methods, and less accurate, though still potentially useful forecasts for the remaining groups. Though the overall benefits of applying GSI-based in-season methods should be formally evaluated, this technique shows promise for providing accurate and timely forecasts for the five Fraser Chinook management units, as additional data are GSI analyzed and can be added to these models.

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Tables and Figures

Table 1. **Conversion chart of statistical weeks to day-month format for weeks that are applicable to this analysis.**

Statistical Week	Period	
19	06-May	12-May
20	13-May	19-May
21	20-May	26-May
22	27-May	02-Jun
23	03-Jun	09-Jun
24	10-Jun	16-Jun
25	17-Jun	23-Jun
26	24-Jun	30-Jun
27	01-Jul	07-Jul
28	08-Jul	14-Jul
29	15-Jul	21-Jul
30	22-Jul	28-Jul
31	29-Jul	04-Aug
32	05-Aug	11-Aug
33	12-Aug	18-Aug
34	19-Aug	25-Aug
35	26-Aug	01-Sep
36	02-Sep	08-Sep
37	09-Sep	15-Sep
38	16-Sep	22-Sep
39	23-Sep	29-Sep
40	30-Sep	06-Oct
41	07-Oct	13-Oct
42	14-Oct	20-Oct
43	21-Oct	27-Oct

Table 2. **Inventory of Fraser Chinook stocks according to Conservation Unit and Management Unit. Stocks that are included in the return and genetic data are indicated.**

Stock Information				Data Availability	
Management Unit	CU ID	CU Name	Stock Name	Return Data	GSI Data
Fall	CK-03	Lower Fraser River_FA_0.3	Harrison	√	√
Fall	CK-9006	Fraser-Cross	Stave	√	√
Fall	CK-9008	Fraser-Harrison fall transplant	Chilliwack	√	√
Spring 42	CK-16	South Thompson-Bessette Creek	Bessette	√	√
Spring 42	CK-16		Duteau		√
Spring 42	CK-17	Lower Thompson	Bonaparte	√	√
Spring 42	CK-17		Coldwater	√	√
Spring 42	CK-17		Deadman	√	√
Spring 42	CK-17		Louis	√	√
Spring 42	CK-17		Nicola	√	√
Spring 42	CK-17		Spius	√	√
Spring 52	CK-04	Lower Fraser River_SP_1.3	Birkenhead	√	√
Spring 52	CK-05	Lower Fraser River-Upper Pitt	Pitt	√	√
Spring 52	CK-08	Middle Fraser-Fraser Canyon	Nahatlatch	√	
Spring 52	CK-10	Middle Fraser River_SP_1.3	Baker	√	√
Spring 52	CK-10		Baezeako		√
Spring 52	CK-10		Blackwater	√	√
Spring 52	CK-10		Bridge	√	√
Spring 52	CK-10		Chilako	√	√
Spring 52	CK-10		Chilcotin Lower	√	√
Spring 52	CK-10		Chilcotin Upper	√	√
Spring 52	CK-10		Cottonwood	√	√
Spring 52	CK-10		Endako	√	√
Spring 52	CK-10		Horsefly	√	
Spring 52	CK-10		McKinley	√	
Spring 52	CK-10		Narcosli	√	
Spring 52	CK-10		Naver	√	
Spring 52	CK-10		Nazko		√
Spring 52	CK-11	Middle Fraser River_SU_1.5	Elkin	√	√

Table 2 cont'd

Management Unit	CU ID	CU Name	Stock Name	Return Data	GSI Data
Spring 52	CK-12	Upper Fraser River	Bowron	√	√
Spring 52	CK-12		Dome	√	√
Spring 52	CK-12		Fontoniko		√
Spring 52	CK-12		Fraser	√	√
Spring 52	CK-12		Goat	√	√
Spring 52	CK-12		Herrick		√
Spring 52	CK-12		Holliday	√	
Spring 52	CK-12		Holmes	√	√
Spring 52	CK-12		Horsey	√	√
Spring 52	CK-12		Indianpoint		√
Spring 52	CK-12		James		√
Spring 52	CK-12		Kenneth		√
Spring 52	CK-12		McGregor	√	√
Spring 52	CK-12		McKale	√	
Spring 52	CK-12		Morkill	√	√
Spring 52	CK-12		Nevin	√	√
Spring 52	CK-12		Ptarmigan		√
Spring 52	CK-12		Salmon (PG)	√	√
Spring 52	CK-12		Slim	√	√
Spring 52	CK-12		Small	√	
Spring 52	CK-12		Swift	√	√
Spring 52	CK-12		Torpy	√	√
Spring 52	CK-12		Twin	√	
Spring 52	CK-12		Walker	√	√
Spring 52	CK-12		Willow	√	√
Spring 52	CK-18	North Thompson_SP_1.3	Blue	√	√
Spring 52	CK-18		Finn	√	√
Spring 52	CK-9006	Fraser-Cross	Chehalis	√	√
Spring 52	CK-14	South Thompson_SU_1.3	Eagle	√	√
Spring 52	CK-14		Salmon (ST)	√	√
Spring 52	CK-14		Scotch	√	
Spring 52	CK-14		Seymour	√	√
Summer 41	CK-07	Maria Slough	Maria Slough	√	√
Summer 41	CK-13	South Thompson_SU_0.3	Adams	√	√
Summer 41	CK-13		Little River	√	√
Summer 41	CK-13		Lower Thompson	√	√
Summer 41	CK-13		South Thompson	√	√

Table 2 cont'd

Management Unit	CU ID	CU Name	Stock Name	Return Data	GSI Data
Summer 41	CK-15	Shuswap River	Lower Shuswap	√	√
Summer 41	CK-15		Middle Shuswap	√	√
Summer 41	CK-15		Wap	√	
Summer 41	CK-82	Upper Adams River	Upper Adams	√	√
Summer 52	CK-06	Lower Fraser River	Big Silver	√	√
Summer 52	CK-06		Chilliwack Su	√	√
Summer 52	CK-06		Douglas	√	
Summer 52	CK-06		Sloquet	√	
Summer 52	CK-06		Tipella	√	
Summer 52	CK-09	Middle Fraser River-Portage	Portage	√	√
Summer 52	CK-11	Middle Fraser River_SU_1.3	Cariboo	√	√
Summer 52	CK-11		Chilko	√	√
Summer 52	CK-11		Kazchek	√	
Summer 52	CK-11		Kuzkwa	√	√
Summer 52	CK-11		Nechako	√	√
Summer 52	CK-11		Pinchi	√	
Summer 52	CK-11		Quesnel	√	√
Summer 52	CK-11		Seton	√	
Summer 52	CK-11		Stellako	√	
Summer 52	CK-11		Stuart	√	√
Summer 52	CK-11		Taseko	√	√
Summer 52	CK-19	North Thompson_SU_1.3	Barriere	√	√
Summer 52	CK-19		Clearwater	√	√
Summer 52	CK-19		Lemieux	√	√
Summer 52	CK-19		Mahood	√	√
Summer 52	CK-19		North Thompson	√	√
Summer 52	CK-19		Raft	√	√

Table 3. **Annual sample size from each net type (single panel, multi panel, and both combined) used by the Albion test fishery (Total), and the number/percent of those samples that were GSI analyzed (Analyzed).**

Year	Single Panel Samples			Multi Panel Samples			All Samples		
	Analyzed	Total	% Analyzed	Analyzed	Total	% Analyzed	Analyzed	Total	% Analyzed
2000	880	1369	64%	709	896	79%	1589	2265	70%
2001	1376	2043	67%	1113	1769	63%	2489	3812	65%
2005	659	1451	45%	524	612	86%	1183	2063	87%
2006	807	816	99%	527	532	99%	1334	1348	99%
2008	954	1613	59%	541	809	67%	1495	2422	62%
2009	1254	1264	99%	722	731	99%	1976	1995	99%
2010	1233	1247	99%	543	550	99%	1776	1797	99%
2011	1373	1393	99%	437	455	96%	1810	1848	98%
2012	526	543	97%	274	274	100%	800	817	98%
2013	624	628	99%	418	421	99%	1042	1049	99%
2014	761	817	93%	605	630	96%	1366	1447	94%

Table 4. **Proportion of annual data points that fall outside the highest probability density region of replicated data for each model type analyzed across available analysis weeks.**

MU	Model	Statistical Week																								
		19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
Spring 42	Linear	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	**10%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Exponential	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	**10%**	0%	0%	0%	0%	0%	0%	0%	0%	**10%**	0%	**10%**	0%	0%	0%
	Allometric	---	0%	0%	0%	0%	0%	0%	0%	**10%**	**10%**	**10%**	0%	**10%**	0%	0%	**10%**	0%	0%	0%	0%	0%	0%	**10%**	0%	0%
Spring 52	Linear	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Exponential	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Allometric	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Summer 52	Linear	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Exponential	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Allometric	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Summer 41	Linear	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Exponential	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Allometric	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Fall	Linear	---	---	---	---	---	---	---	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Exponential	---	---	---	---	---	---	---	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Allometric	---	---	---	---	---	---	---	---	---	---	---	---	---	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 5. **Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) performance measure values calculated for the Spring 4_2 management unit for each model form (columns) and analysis week (rows) in the cross-validation analysis.**

Week	MPE				MAPE				RMSE			
	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite
19	--	--	--	--	--	--	--	--	--	--	--	--
20	--	--	--	--	--	--	--	--	--	--	--	--
21	--	--	--	--	--	--	--	--	--	--	--	--
22	--	--	--	--	--	--	--	--	--	--	--	--
23	0.35	0.45	**0.21**	0.28	**0.54**	2.47	**0.49**	**0.53**	7965	23113	7603	8887
24	0.43	0.84	0.27	0.37	0.63	0.77	0.59	0.65	11959	55313	10713	13983
25	0.39	0.89	**0.22**	0.33	0.56	1.17	**0.51**	0.59	11620	65024	**6514**	12395
26	0.39	0.84	**0.21**	0.33	0.57	1.18	**0.52**	0.60	11684	61043	**6121**	11945
27	0.29	**0.21**	0.23	0.25	**0.52**	1.15	0.57	**0.53**	**5689**	6808	7195	**5925**
28	0.30	**0.20**	0.27	0.26	**0.54**	0.55	0.63	0.57	**5863**	**6328**	7806	**6378**
29	0.31	**0.21**	0.26	0.27	**0.54**	0.56	0.62	0.57	**5905**	**6341**	7642	**6417**
30	0.37	0.26	0.33	0.33	0.61	0.56	0.71	0.65	6805	7672	8650	7475
31	0.36	0.25	0.33	0.31	0.61	0.65	0.71	0.65	**6599**	7608	8666	7404
32	0.37	0.23	0.33	0.32	0.61	0.65	0.72	0.66	**6766**	7824	8890	7605
33	0.38	**0.22**	0.33	0.32	0.61	0.64	0.73	0.66	6953	8228	9005	7736
34	0.38	**0.22**	0.35	0.33	0.61	0.64	0.75	0.68	7034	9119	9215	8032
35	0.40	0.24	0.37	0.35	0.62	0.66	0.77	0.69	7102	9132	9361	8236
36	0.39	0.23	0.38	0.34	0.63	0.67	0.77	0.69	7175	9419	9347	8365
37	0.39	0.23	0.36	0.33	0.63	0.68	0.77	0.70	7215	9623	9376	8441
38	0.39	0.23	0.37	0.34	0.63	0.68	0.77	0.70	7210	9566	9425	8528
39	0.39	0.23	0.37	0.34	0.63	0.68	0.77	0.70	7144	9301	9298	8305
40	0.39	0.23	0.36	0.34	0.63	0.68	0.76	0.70	7136	9230	9323	8342
41	0.39	0.24	0.37	0.35	0.63	0.68	0.77	0.69	7129	9298	9294	8225
42	0.38	0.23	0.36	0.33	0.63	0.67	0.77	0.70	7149	9356	9439	8401

Table 6. Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) performance measure values calculated for the Spring 5_2 management unit for each model form (columns) and analysis week (rows) in the cross-validation analysis.

Week	MPE				MAPE				RMSE			
	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite
19	--	--	--	--	--	--	--	--	--	--	--	--
20	0.04	0.04	**0.00**	**0.02**	**0.16**	**0.18**	**0.20**	**0.2**	**5204**	**7578**	**5983**	**5435**
21	0.07	0.06	**0.03**	0.05	0.21	0.23	**0.18**	**0.2**	**7305**	8898	**6481**	**6919**
22	0.12	0.13	0.04	0.08	0.29	0.34	0.22	0.3	11281	17749	10663	11122
23	0.14	0.18	0.04	0.09	0.31	0.40	0.22	0.3	12338	24770	10161	11784
24	0.13	0.16	0.05	0.09	0.31	0.38	0.22	0.3	11859	21754	9820	11433
25	0.11	0.13	0.04	0.08	0.29	0.33	0.20	0.2	11043	18107	8883	10497
26	0.08	0.06	**0.02**	0.05	0.23	0.23	**0.17**	0.2	8987	10693	**7709**	8500
27	0.08	0.06	**0.03**	0.05	0.23	0.23	**0.19**	0.2	9211	10575	**7826**	8820
28	0.10	0.08	**0.03**	0.07	0.27	0.28	0.20	0.2	10383	12988	8265	9953
29	0.11	0.10	**0.03**	0.07	0.28	0.31	0.21	0.3	11160	15402	8557	10641
30	0.12	0.11	0.04	0.08	0.28	0.31	0.21	0.2	11097	15199	8637	10610
31	0.10	0.08	0.03	0.07	0.27	0.28	0.21	0.2	10272	12416	8466	9789
32	0.08	0.06	**0.03**	0.05	0.24	0.25	**0.19**	0.2	9252	10528	8120	8895
33	0.11	0.10	0.04	0.07	0.27	0.30	0.20	0.2	10227	14488	8265	9644
34	0.10	0.10	**0.03**	0.07	0.27	0.31	0.20	0.2	10376	15162	8315	9846
35	0.11	0.11	0.04	0.07	0.27	0.31	0.20	0.2	10288	15108	8288	9776
36	0.10	0.11	0.03	0.07	0.27	0.31	0.20	0.2	10411	15570	8325	9970
37	0.11	0.10	0.03	0.07	0.27	0.31	0.20	0.2	10335	15105	8283	9756
38	0.11	0.11	0.04	0.08	0.28	0.31	0.20	0.2	10366	14989	8342	9847
39	0.11	0.11	0.04	0.08	0.28	0.31	0.20	0.2	10400	15516	8336	9927
40	0.11	0.11	0.04	0.07	0.27	0.31	0.20	0.2	10413	15384	8402	9933
41	0.11	0.10	**0.03**	0.07	0.28	0.31	0.20	0.2	10368	14987	8294	9792
42	0.11	0.11	0.04	0.07	0.28	0.31	0.20	0.2	10373	15153	8284	9867

Table 7. **Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) performance measure values calculated for the Summer 5_2 management unit for each model form (columns) and analysis week (rows) in the cross-validation analysis.**

Week	MPE				MAPE				RMSE			
	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite
19	--	--	--	--	--	--	--	--	--	--	--	--
20	--	--	--	--	--	--	--	--	--	--	--	--
21	--	--	--	--	--	--	--	--	--	--	--	--
22	--	--	--	--	--	--	--	--	--	--	--	--
23	--	--	--	--	--	--	--	--	--	--	--	--
24	--	--	--	--	--	--	--	--	--	--	--	--
25	0.22	1.13	0.06	0.16	0.39	1.32	0.20	0.32	19952	136263	8207	16572
26	0.24	1.87	0.04	0.19	0.39	2.05	0.18	0.34	24030	241146	6666	20299
27	0.18	0.60	0.03	0.14	0.32	0.78	0.18	0.30	17392	76020	6323	15775
28	0.11	0.20	**0.02**	0.09	0.26	0.38	0.21	0.25	10832	24963	6966	9943
29	0.07	0.06	**0.02**	0.05	0.21	0.23	0.19	0.21	6932	8885	6740	6782
30	0.05	0.04	**0.02**	0.04	0.19	0.20	0.18	0.19	6583	7105	6301	6522
31	0.07	0.06	**0.02**	0.05	0.21	0.23	0.16	0.19	7506	9255	5956	7198
32	0.08	0.10	**0.02**	0.06	0.23	0.26	0.17	0.21	8736	12777	6250	8519
33	0.08	0.08	0.03	0.05	0.21	0.24	0.16	0.20	8003	10552	6258	7839
34	0.07	0.06	0.03	0.05	0.19	0.21	**0.15**	0.17	7065	8209	6021	6840
35	0.07	0.06	0.03	0.05	0.19	0.21	**0.15**	0.17	6809	7603	**5933**	6577
36	0.06	0.05	0.03	0.04	0.18	0.20	**0.14**	0.17	6607	7444	**5848**	6446
37	0.06	0.05	0.03	0.04	0.18	0.20	**0.14**	0.16	6568	7338	**5750**	6338
38	0.06	0.05	0.03	0.04	0.18	0.20	**0.14**	0.17	6595	7380	**5794**	6393
39	0.06	0.05	0.03	0.04	0.17	0.19	**0.14**	0.16	6499	7281	**5778**	6368
40	0.06	0.05	0.03	0.04	0.18	0.20	**0.14**	0.16	6581	7395	**5816**	6364
41	0.06	0.05	0.03	0.05	0.18	0.19	**0.14**	0.16	6577	7288	**5806**	6388
42	0.06	0.05	0.03	0.04	0.18	0.20	**0.14**	0.17	6583	7338	**5818**	6384

Table 8. **Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) performance measure values calculated for the Summer 4_1 management unit for each model form (columns) and analysis week (rows) in the cross-validation analysis.**

Week	MPE				MAPE				RMSE			
	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite
19	--	--	--	--	--	--	--	--	--	--	--	--
20	--	--	--	--	--	--	--	--	--	--	--	--
21	--	--	--	--	--	--	--	--	--	--	--	--
22	--	--	--	--	--	--	--	--	--	--	--	--
23	--	--	--	--	--	--	--	--	--	--	--	--
24	--	--	--	--	--	--	--	--	--	--	--	--
25	--	--	--	--	--	--	--	--	--	--	--	--
26	0.29	0.43	0.12	0.24	0.50	0.68	0.40	0.48	89204	150599	63285	87050
27	0.44	1.10	0.12	0.35	0.65	1.36	0.43	0.61	128674	398600	61450	114940
28	0.36	0.54	0.12	0.27	0.58	0.80	0.42	0.53	102276	188873	61273	91918
29	0.31	0.36	0.12	0.23	0.54	0.62	0.41	0.49	91315	125258	60436	79154
30	0.26	0.23	0.12	0.19	0.49	0.50	0.41	0.46	77356	85140	61169	70095
31	0.25	0.20	0.13	0.19	0.48	0.47	0.41	0.45	73227	76349	60884	67686
32	0.21	0.15	0.12	0.16	0.44	0.42	0.41	0.42	65601	64104	60712	62487
33	0.20	0.14	0.12	0.16	0.42	0.40	0.39	0.41	61490	60066	58341	60429
34	0.18	0.12	0.12	0.15	0.40	0.39	0.39	0.40	59211	59345	59088	59806
35	0.18	**0.11**	**0.11**	0.14	0.39	**0.38**	**0.37**	**0.38**	58470	58573	**58065**	59145
36	0.17	**0.11**	**0.11**	0.12	0.40	**0.38**	**0.38**	**0.38**	58394	58784	59149	**58152**
37	0.19	0.12	0.12	0.14	0.41	**0.38**	**0.38**	0.39	58413	58329	58916	58939
38	0.18	**0.11**	**0.11**	0.13	0.40	**0.38**	**0.38**	**0.38**	**58309**	**58256**	59185	**58122**
39	0.19	0.12	0.12	0.14	0.41	0.39	0.39	0.40	58561	58566	59370	58980
40	0.19	0.13	0.13	0.15	0.41	**0.38**	0.39	0.40	**58106**	**57801**	58618	**58582**
41	0.19	0.12	0.12	0.14	0.41	0.39	0.39	0.40	58847	58846	59854	59227
42	0.19	0.12	0.12	0.15	0.41	0.39	0.39	0.40	59272	59311	59353	59054

Table 9. **Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) performance measure values calculated for the Fall management unit for each model form (columns) and analysis week (rows) in the cross-validation analysis.**

Week	MPE				MAPE				RMSE			
	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite	Linear	Exponential	Allometric	Composite
19	--	--	--	--	--	--	--	--	--	--	--	--
20	--	--	--	--	--	--	--	--	--	--	--	--
21	--	--	--	--	--	--	--	--	--	--	--	--
22	--	--	--	--	--	--	--	--	--	--	--	--
23	--	--	--	--	--	--	--	--	--	--	--	--
24	--	--	--	--	--	--	--	--	--	--	--	--
25	--	--	--	--	--	--	--	--	--	--	--	--
26	--	--	--	--	--	--	--	--	--	--	--	--
27	--	--	--	--	--	--	--	--	--	--	--	--
28	--	--	--	--	--	--	--	--	--	--	--	--
29	--	--	--	--	--	--	--	--	--	--	--	--
30	--	--	--	--	--	--	--	--	--	--	--	--
31	--	--	--	--	--	--	--	--	--	--	--	--
32	--	--	--	--	--	--	--	--	--	--	--	--
33	--	--	--	--	--	--	--	--	--	--	--	--
34	-0.28	-0.04	**0.02**	**-0.01**	0.71	0.40	0.40	0.41	232073	78754	62734	73401
35	-0.07	**-0.02**	0.05	**0.01**	0.50	0.38	0.36	0.38	125428	72766	57018	70432
36	0.10	0.06	0.06	0.07	0.38	0.35	**0.31**	0.34	59562	56716	49905	54348
37	0.14	**0.10**	0.08	0.10	0.37	0.35	0.32	0.35	53794	53018	48239	51434
38	0.13	0.08	0.05	0.09	0.35	0.34	**0.31**	0.33	50370	50812	**46738**	48138
39	0.14	0.10	0.05	0.10	0.36	0.34	0.33	0.34	49307	49525	47468	47908
40	0.12	0.08	**0.04**	0.08	0.34	0.33	0.35	0.33	47190	48031	49426	47309
41	0.09	0.05	**0.02**	0.06	**0.31**	**0.31**	0.35	**0.32**	**44358**	**45259**	51087	**46301**
42	0.09	**0.04**	**0.02**	0.05	**0.31**	**0.30**	0.35	**0.32**	**43903**	**44528**	50806	**45493**

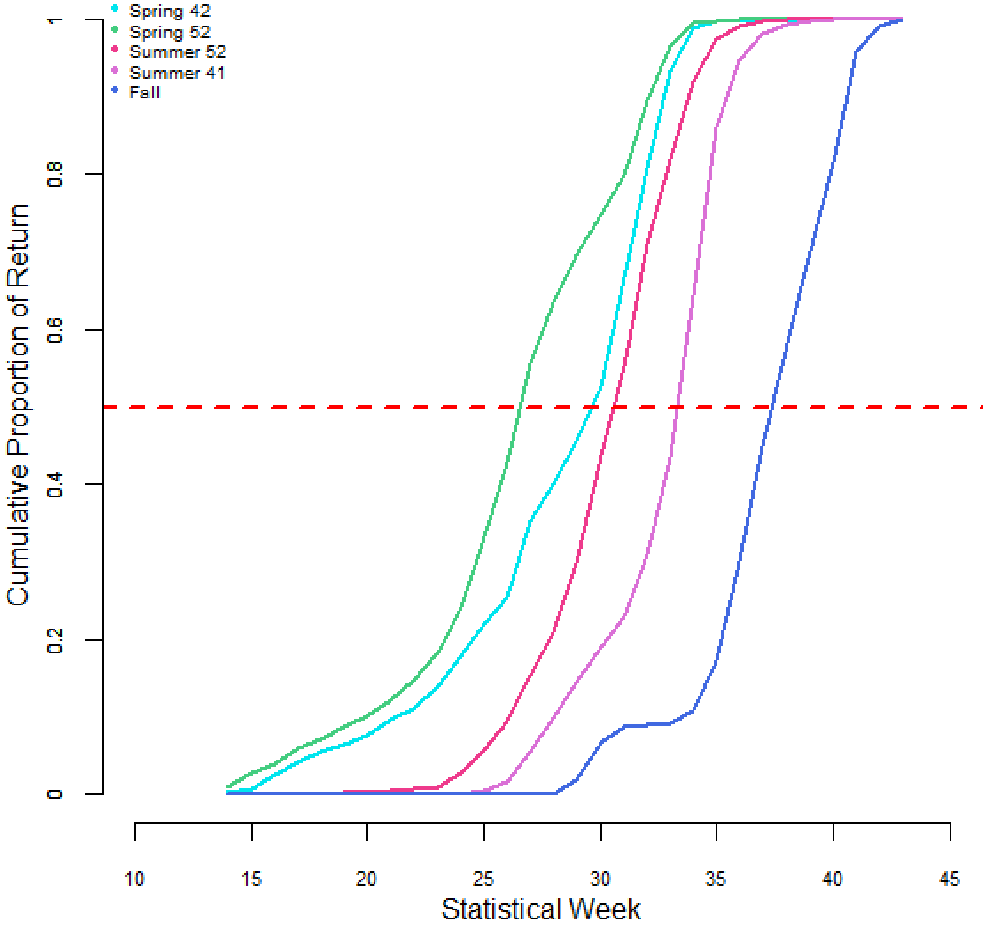


Figure 1. Average cumulative run timing curves for each Fraser Chinook management unit based on GSI analyzed catch data from the Albion test fishery. The red dashed line indicates the point at which 50% of the management unit has migrated past Albion.

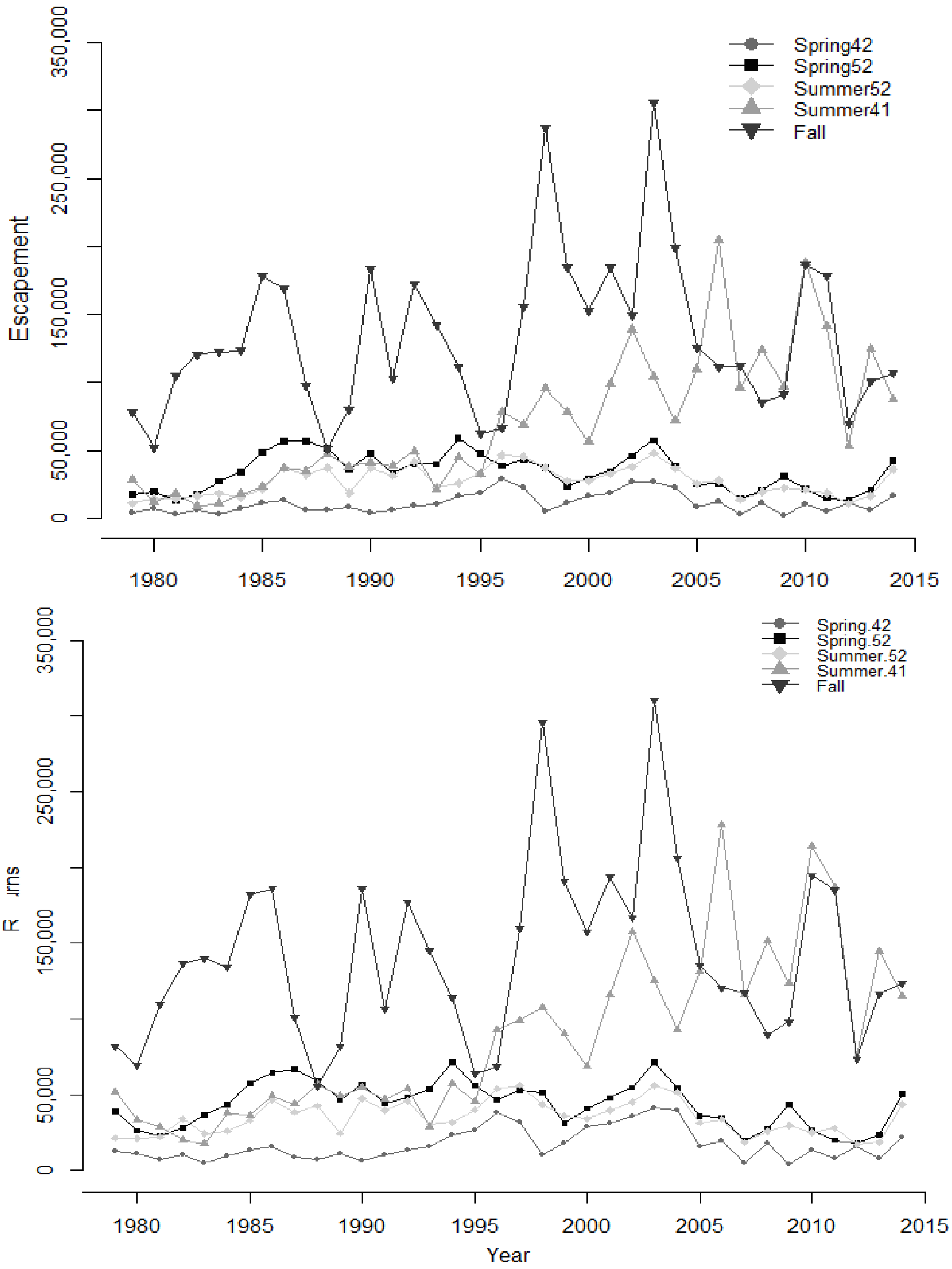


Figure 2. **Time series of escapements (top panel) and returns (bottom panel) for Fraser Chinook management units from 1979 to present. Return estimates are reconstructed to the mouth of the Fraser River using escapement and catch estimates.**

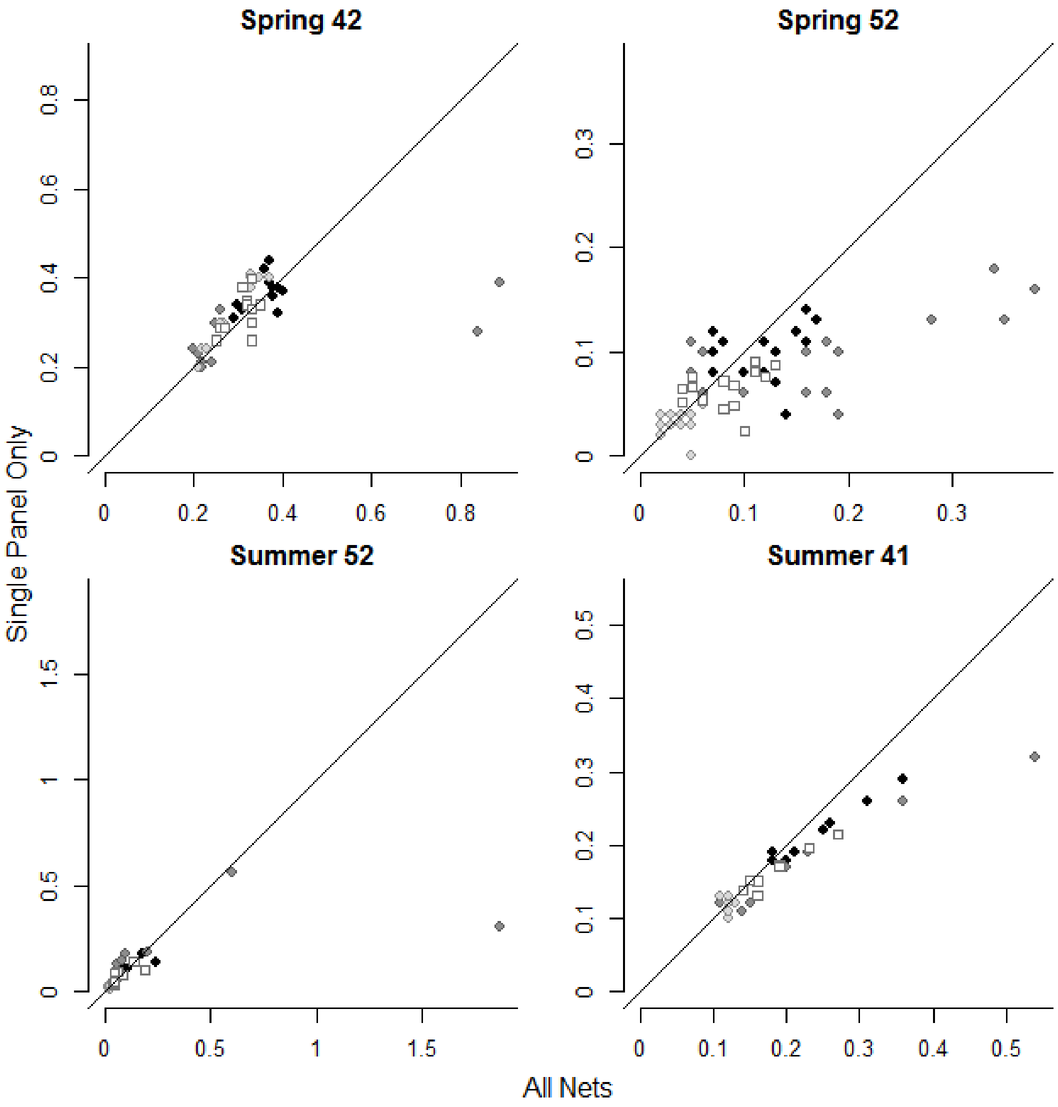


Figure 3. MPE performance measure values for models using CPUE indices calculated from all of the data (x-axis), versus only data from the single panel net (y-axis). Black dots represent the MAPE for linear models, grey circles are exponential models, light grey circles are allometric models, and white squares are composite models.

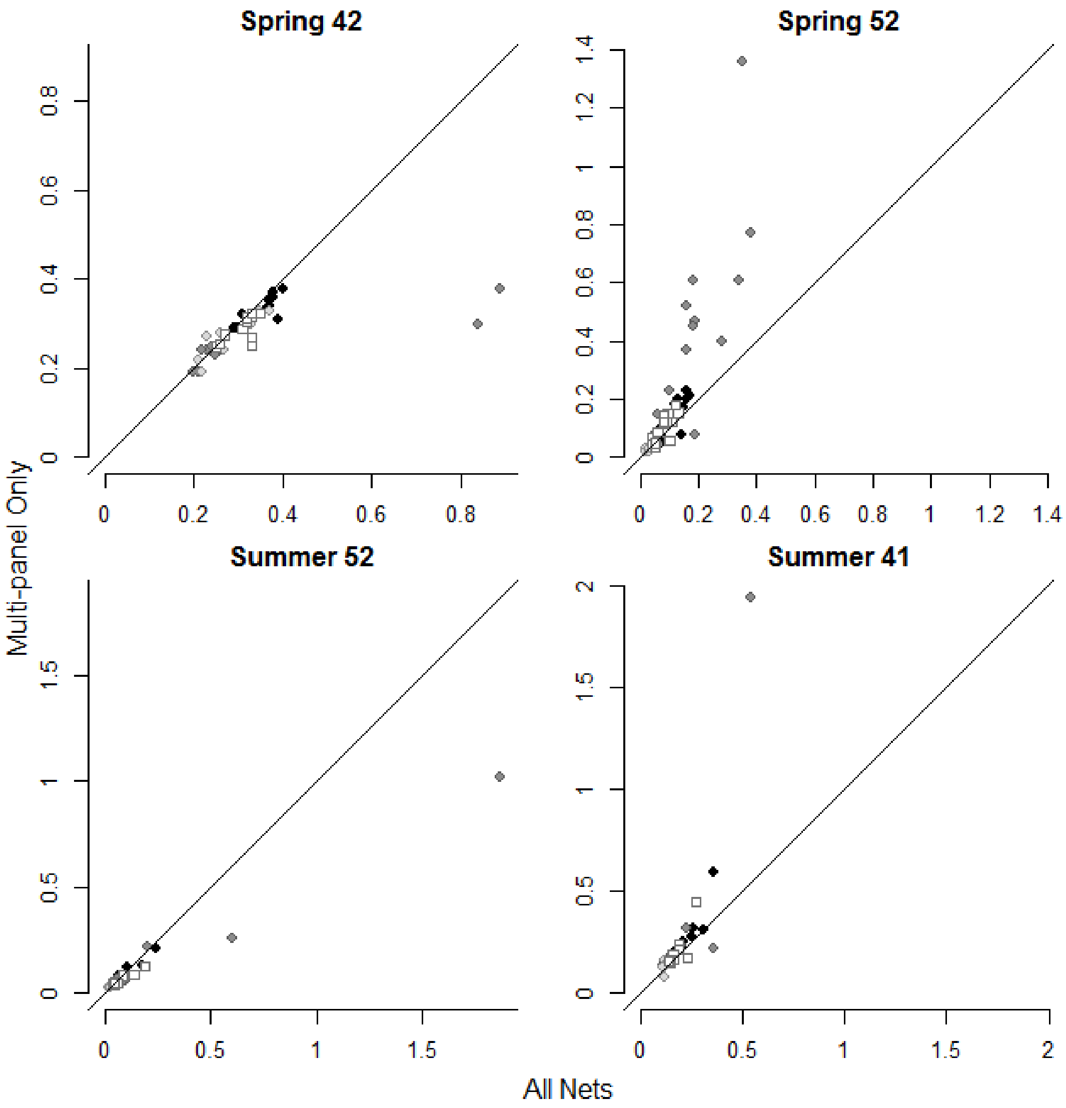


Figure 4. MPE performance measure values for models using CPUE indices calculated from all of the data (x-axis), versus only data from the multi-panel net (y-axis). Black dots represent the MAPE for linear models, grey circles are exponential models, light grey circles are allometric models, and white squares are composite models.

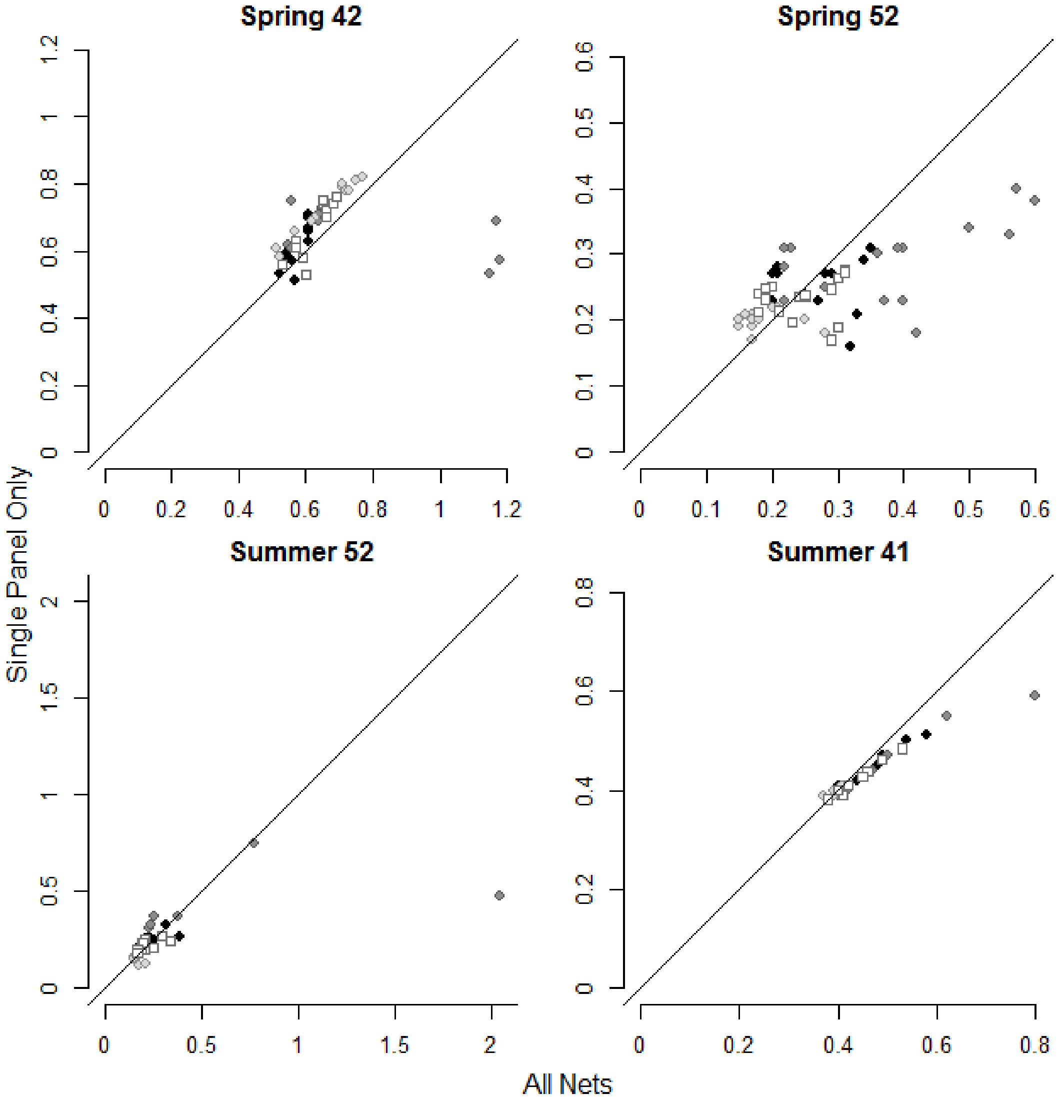


Figure 5. MAPE performance measure values for models using CPUE indices calculated from all of the data (x-axis), versus only data from the single panel net (y-axis). Black dots represent the MAPE for linear models, grey circles are exponential models, light grey circles are allometric models, and white squares are composite models.

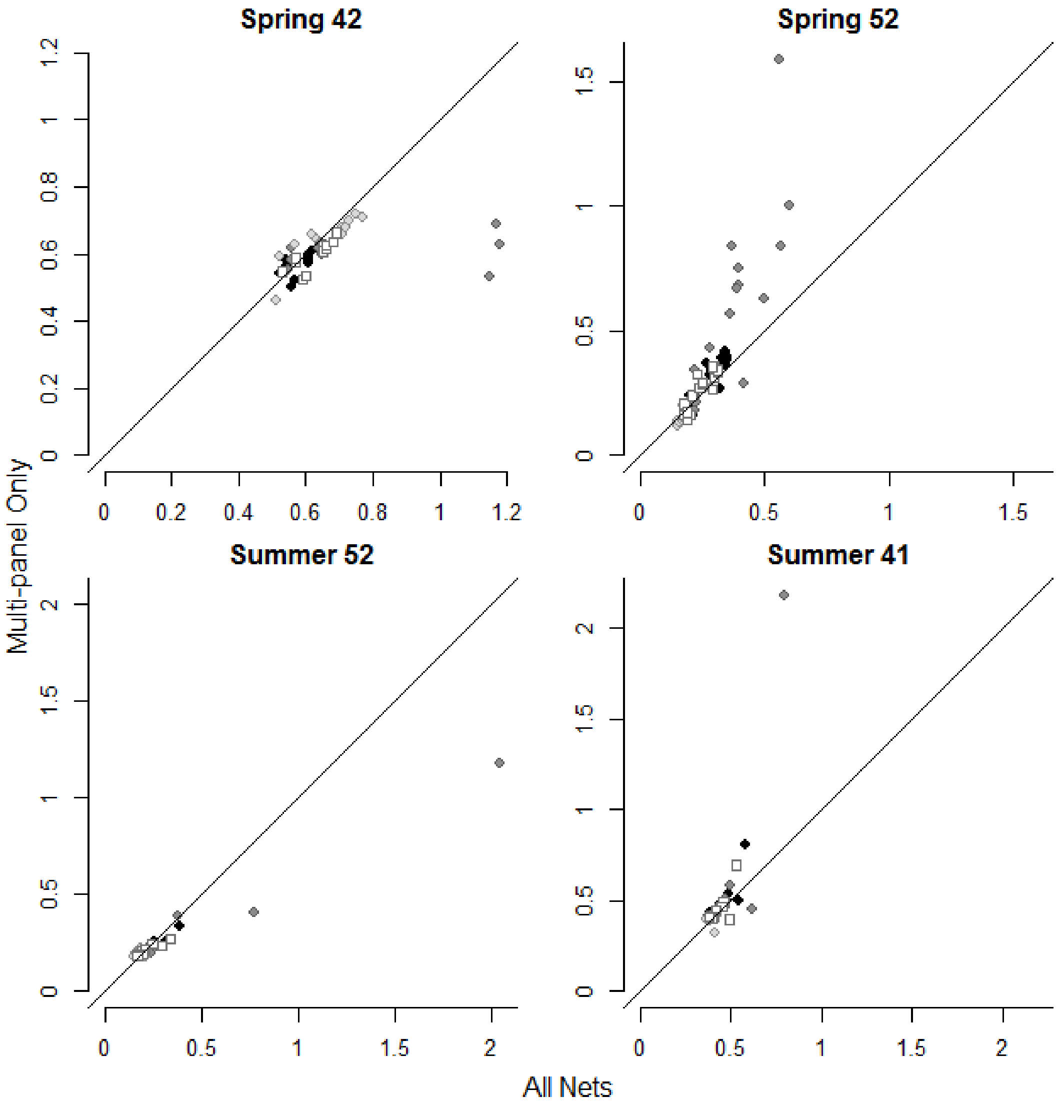


Figure 6. MAPE performance measure for models using CPUE indices calculated from all of the data (x-axis), versus only data from the multi-panel net (y-axis). Black dots represent the MAPE for linear models, grey circles are exponential models, light grey circles are allometric models, and white squares are composite models.

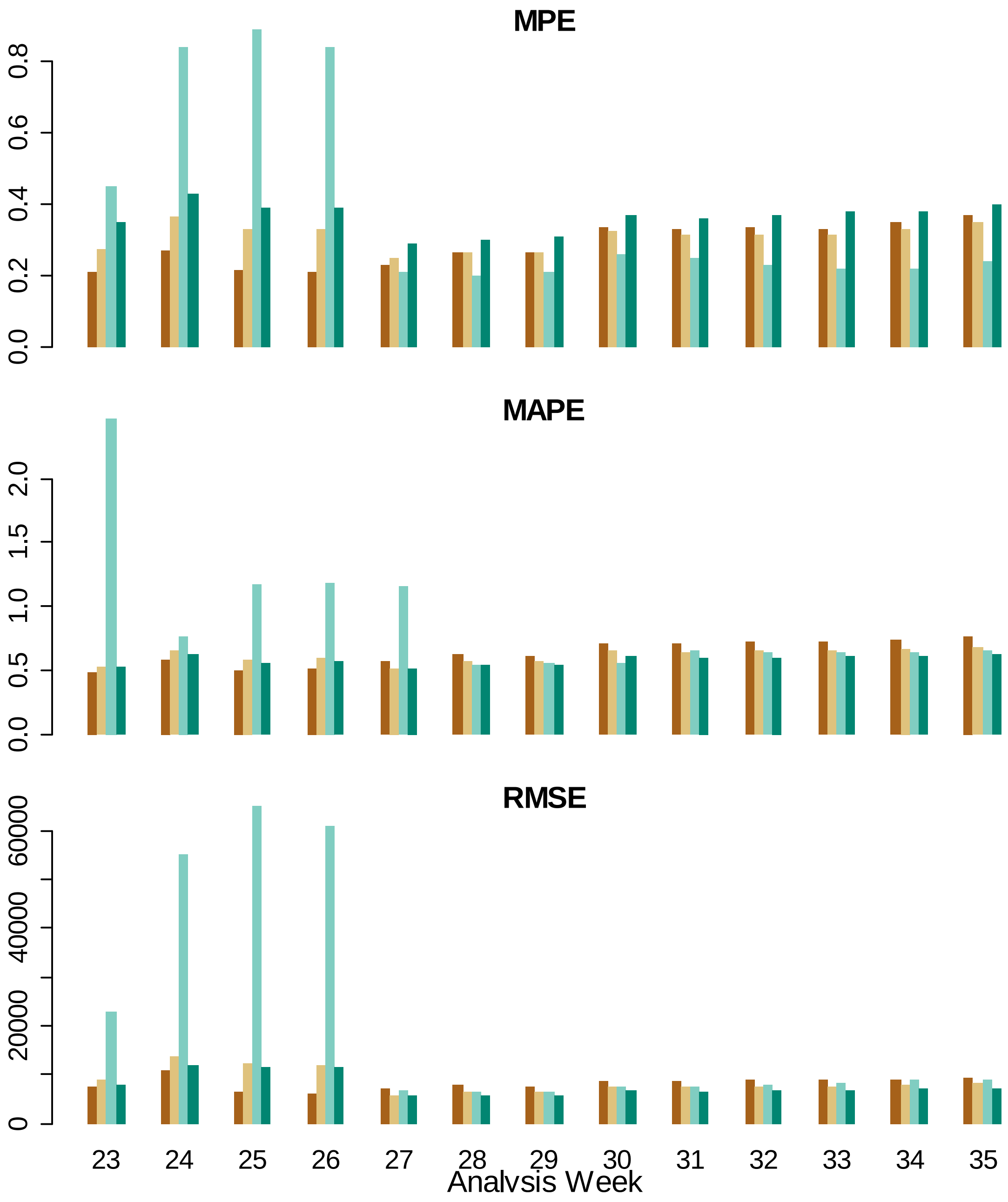


Figure 7. **Weekly performance of Spring 4_2 Chinook forecasting models up to analysis week 35 according to mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE). Models are represented by the following colours: dark brown - allometric model; light brown - composite models; light blue - exponential models; dark blue - linear models.**

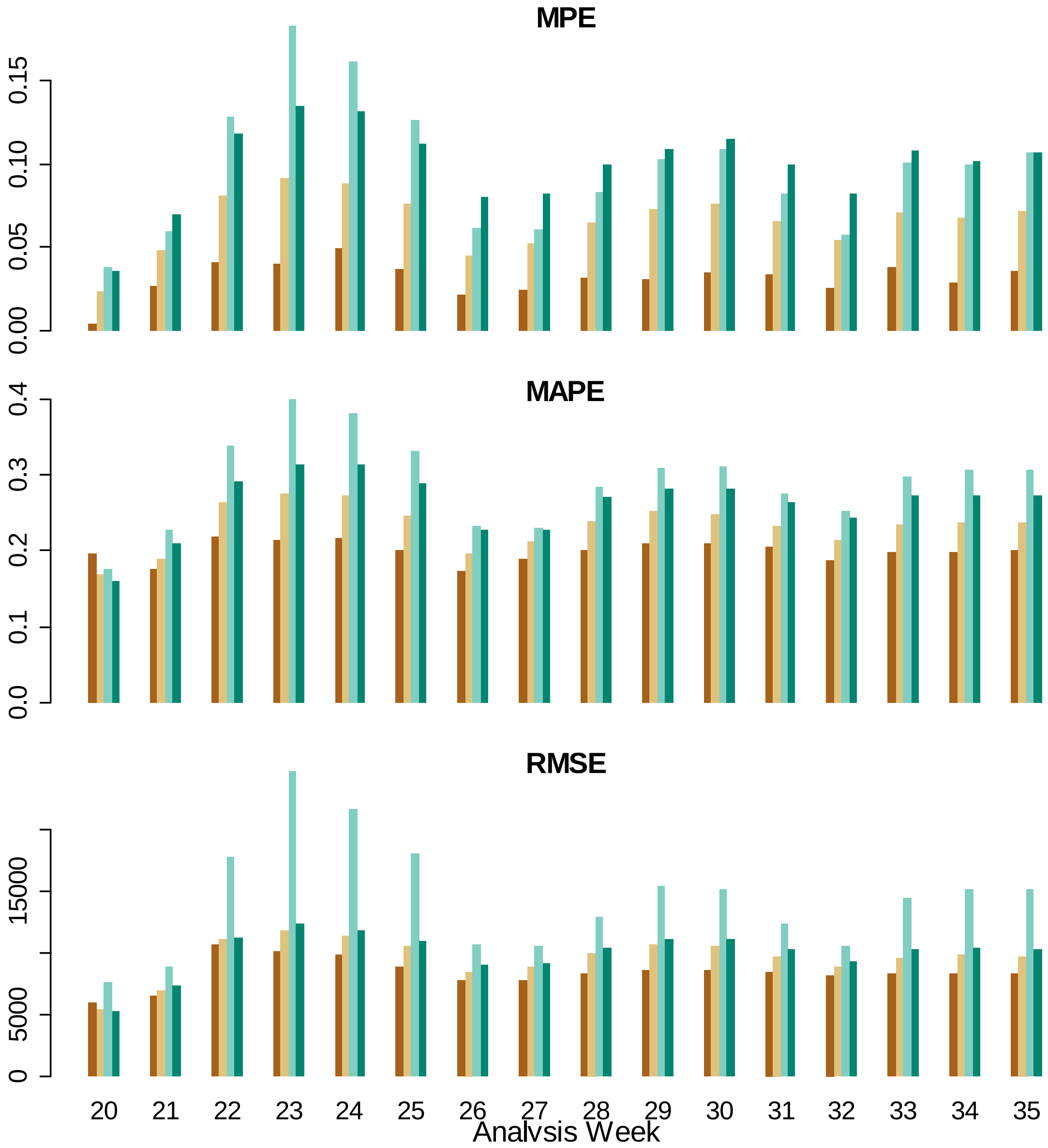


Figure 8. Weekly performance of Spring 5_2 Chinook forecasting models up to analysis week 35 according to mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE). Models are represented by the following colours: dark brown - allometric model; light brown - composite models; light blue - exponential models; dark blue - linear models.

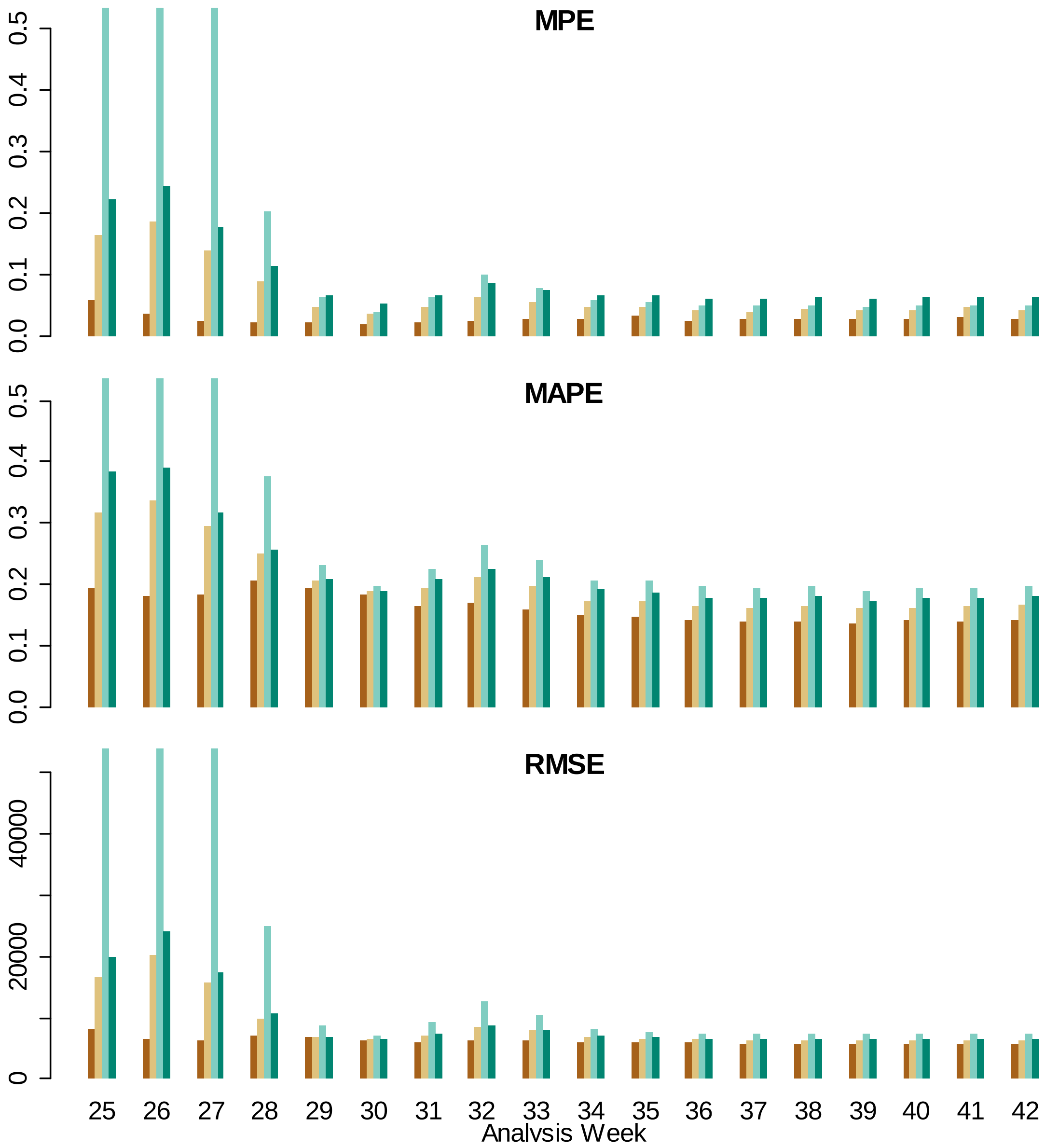


Figure 9. **Weekly performance of Summer 5_2 Chinook forecasting models across analysis weeks according to mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE). Models are represented by the following colours: dark brown - allometric model; light brown - composite models; light blue - exponential models; dark blue - linear models. Maximum values of all performance measures for the exponential model have been constrained for presentation purposes.**

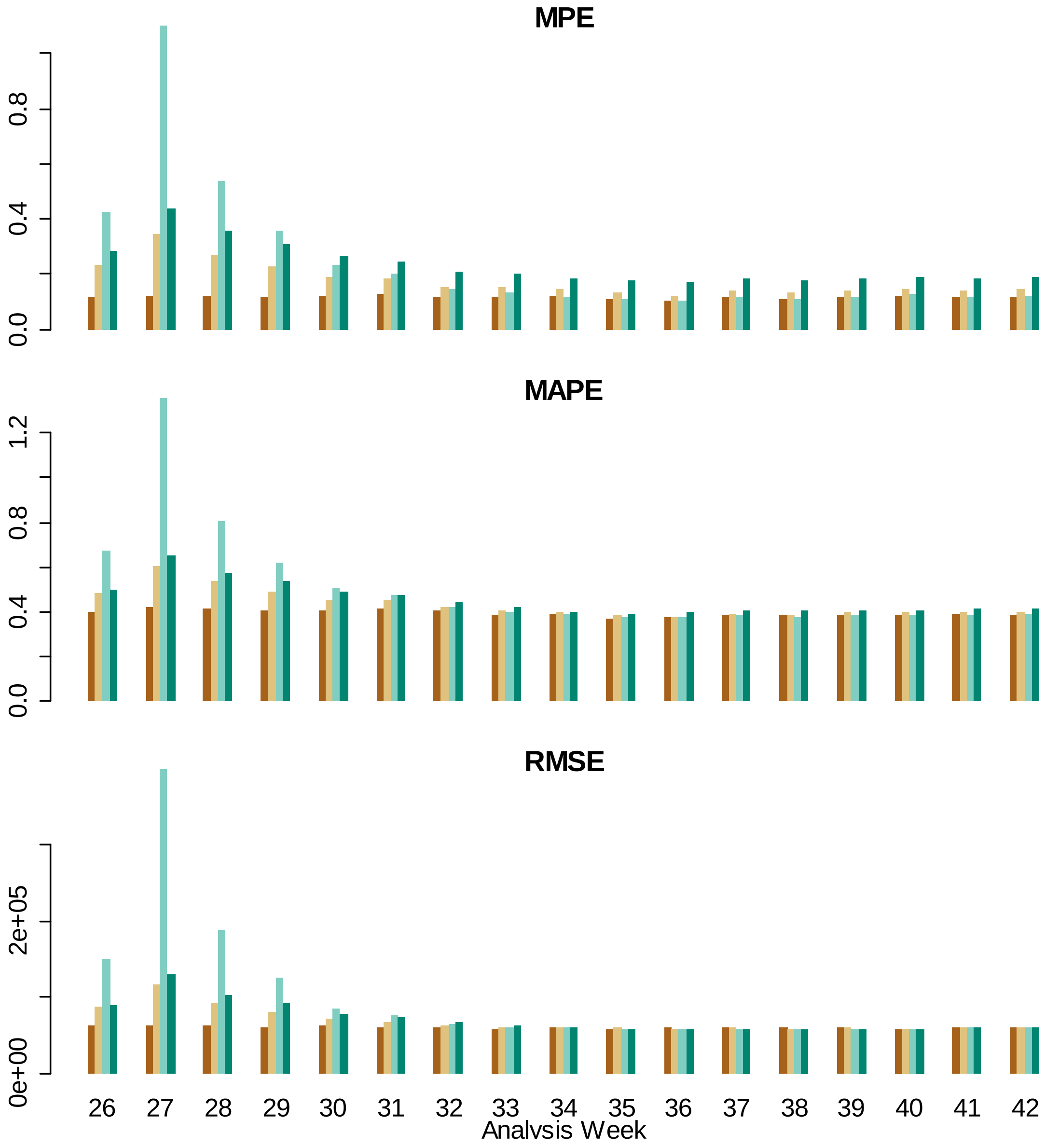


Figure 10. Weekly performance of Summer 41 Chinook forecasting models across analysis weeks according to mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE). Models are represented by the following colours: dark brown - allometric model; light brown - composite models; light blue - exponential models; dark blue - linear models.

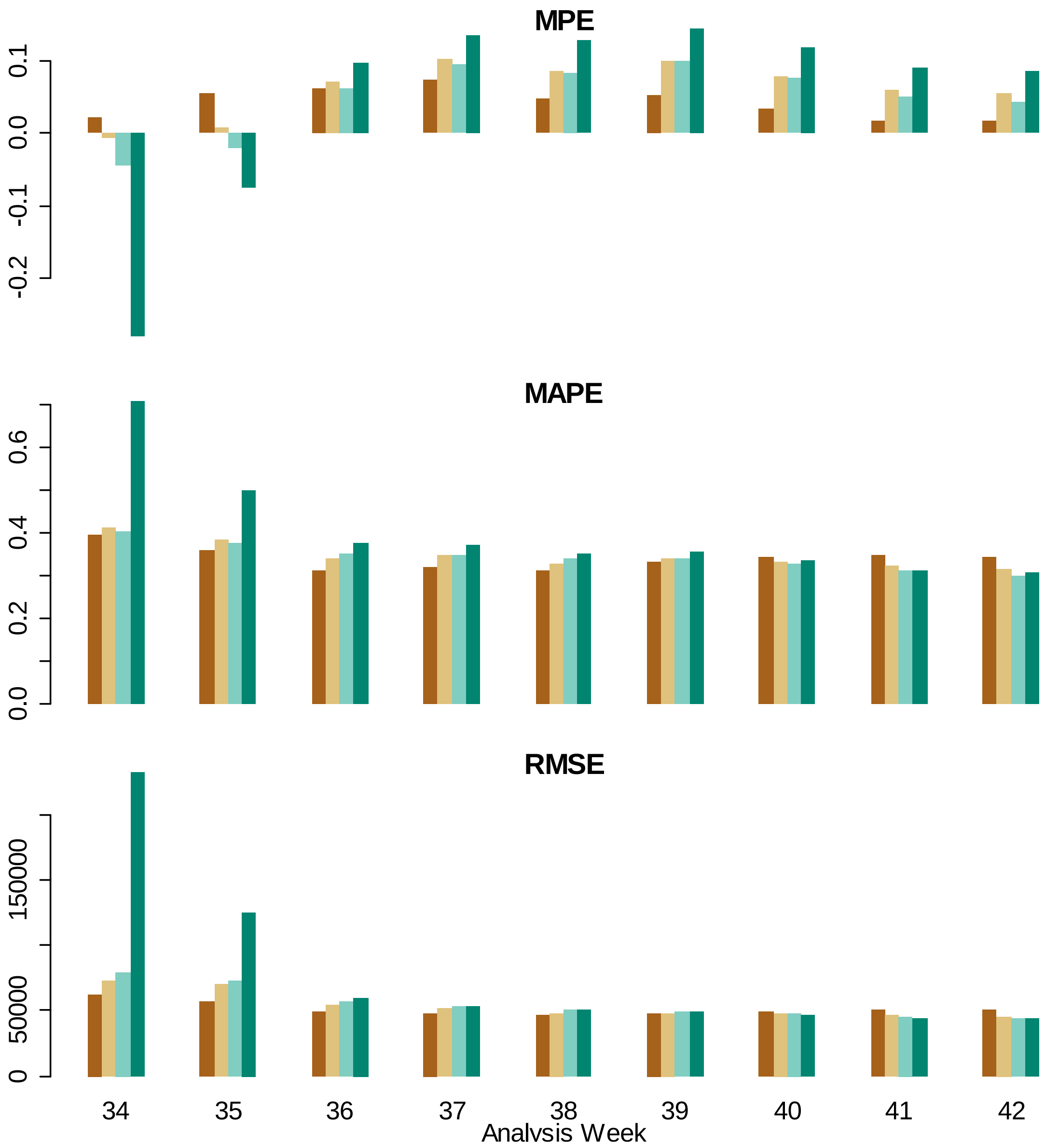


Figure 11. Weekly performance of Fall Chinook forecasting models across analysis weeks according to mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE). Models are represented by the following colours: dark brown - allometric model; light brown - composite models; light blue - exponential models; dark blue - linear models.

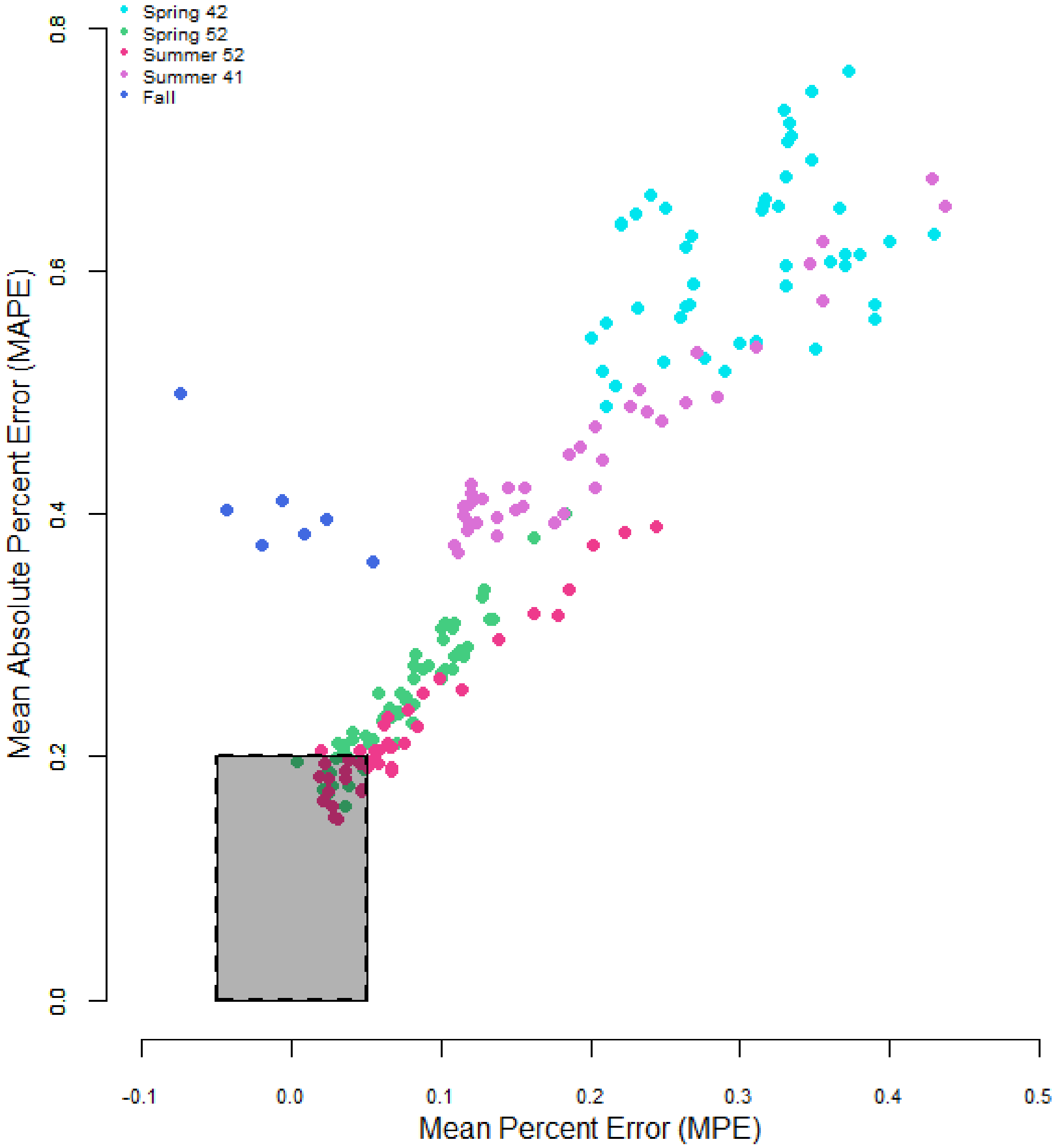


Figure 12. MPE (x-axis) and MAPE (y-axis) performance measures for all Fraser Chinook management unit forecasts across analysis weeks and model forms. The grey box in the lower left corner indicates accuracy and bias benchmarks set by the current Spring and Summer 52 Chinook in-season methods (MAPE < 18%, MPE < 5%).

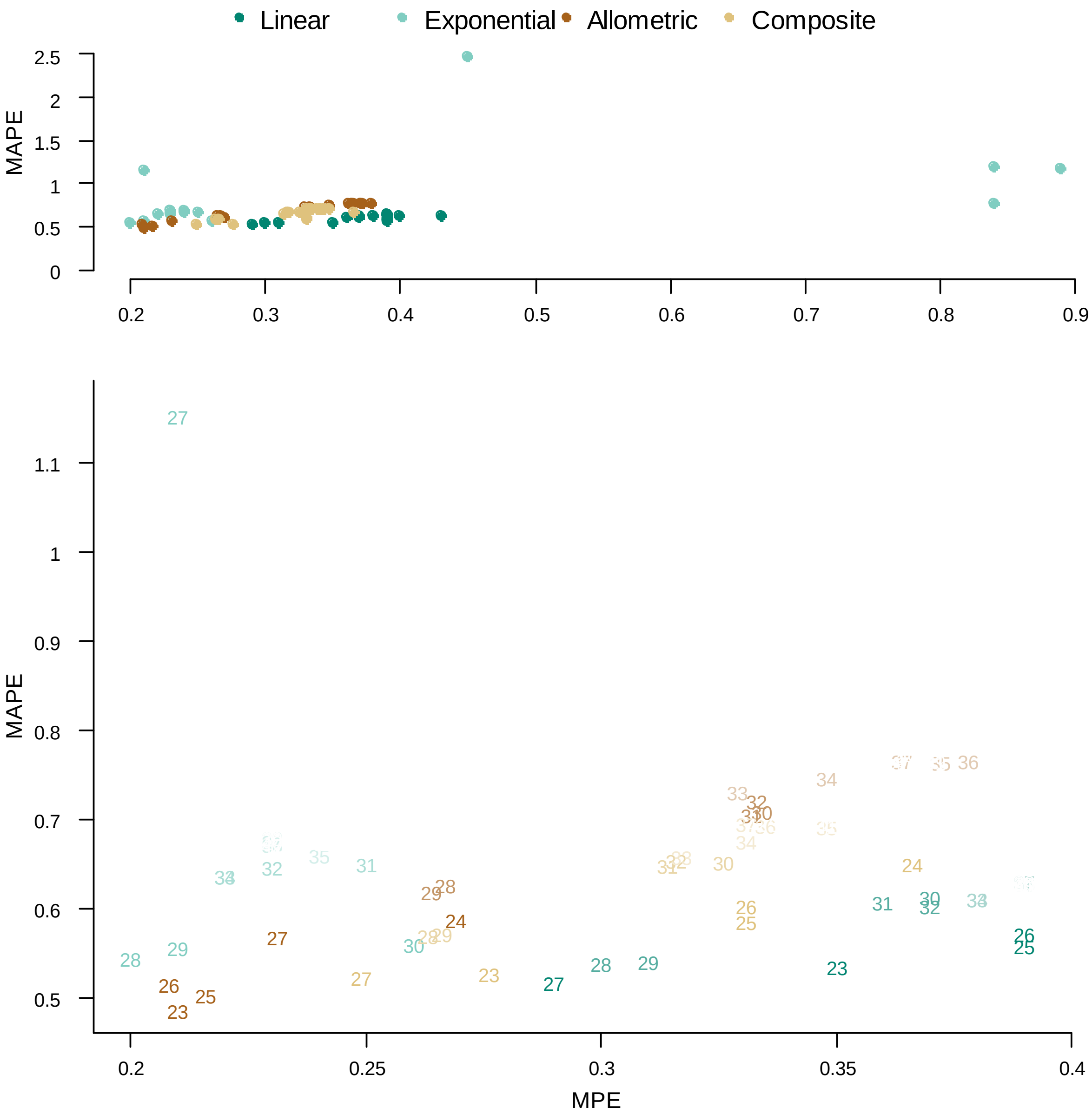


Figure 13. **In-season forecast trade-offs for Spring 4_2 Chinook, between mean percent error (MPE), mean absolute percent error (MAPE) and availability. The top panel presents performance measures for all Spring 4_2 forecasts, colour-coded as follows: dark blue-linear models; light blue-exponential models; dark brown-allometric models; light brown-composite models. The bottom panel focuses on the best performing models, which are labelled according to analysis week, colour-coded as above, and colour-graded with earlier weeks appearing darker and later weeks appearing lighter.**

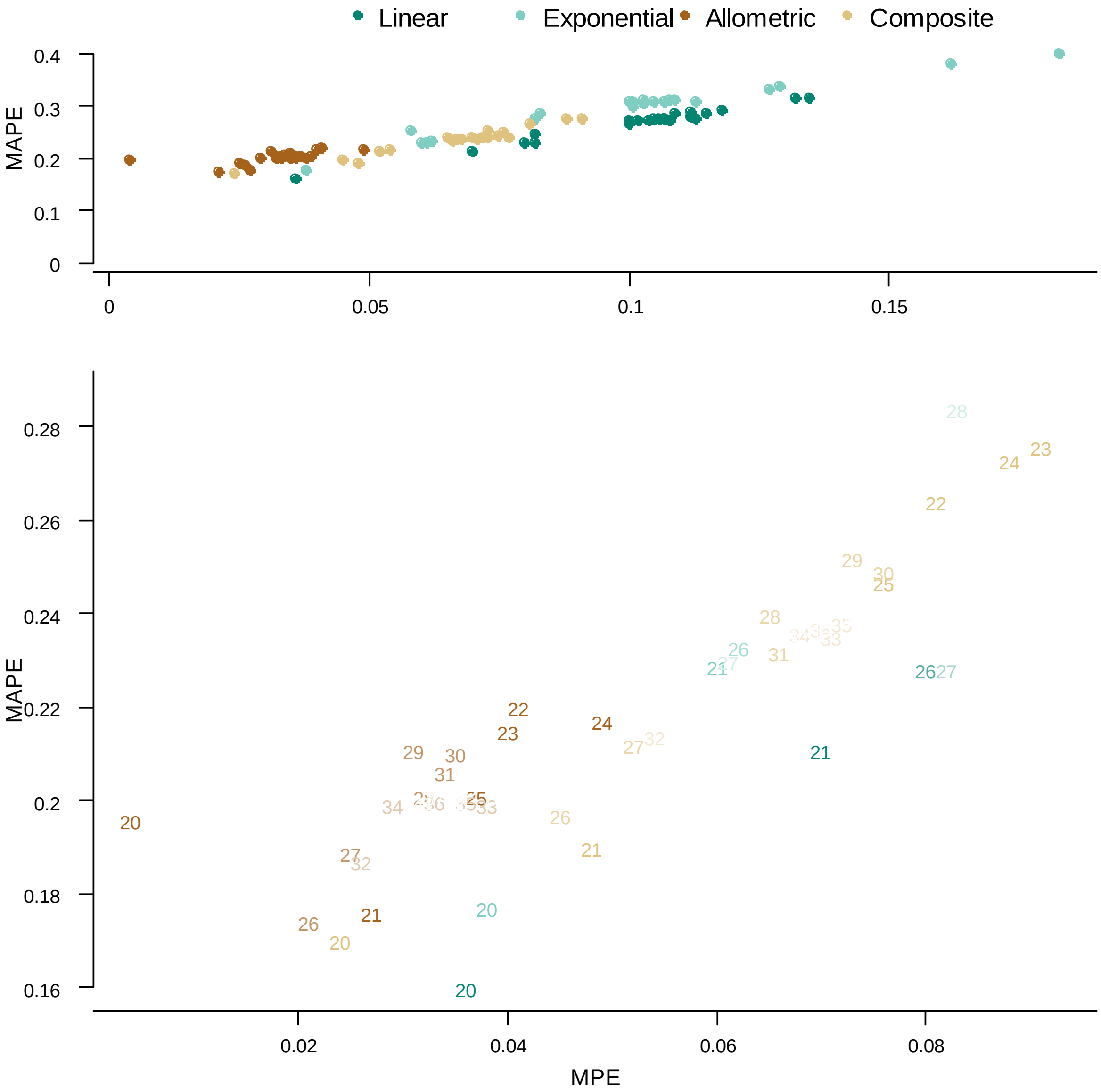


Figure 14. In-season forecast trade-offs for Spring 5_2 Chinook, between mean percent error (MPE), mean absolute percent error (MAPE) and availability. The top panel presents performance measures for all Spring 5_2 forecasts, colour-coded as follows: dark blue-linear models; light blue-exponential models; dark brown-allometric models; light brown-composite models. The bottom panel focuses on the best performing models, which are labelled according to analysis week, colour-coded as above, and colour-graded with earlier weeks appearing darker and later weeks appearing lighter.

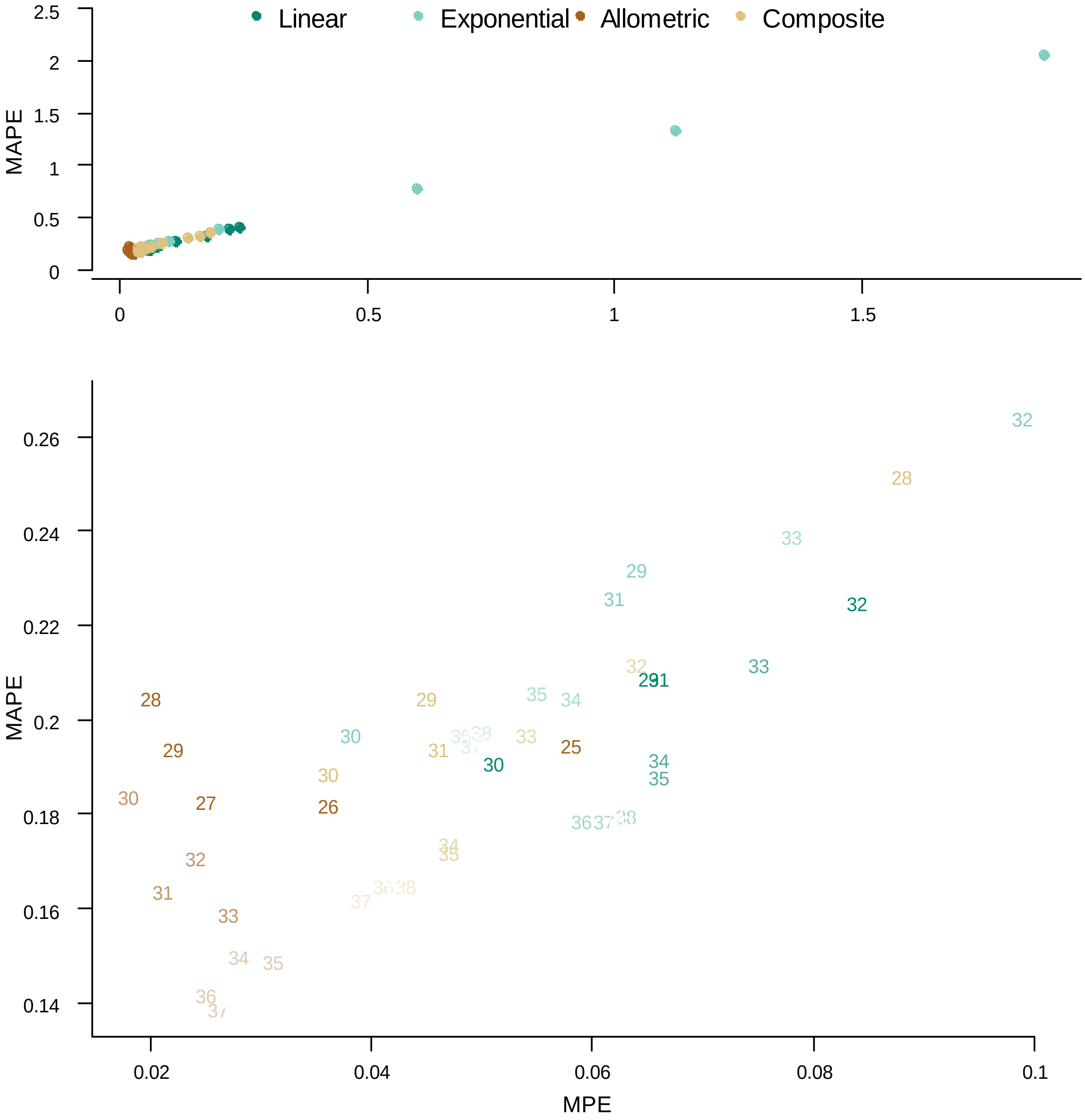


Figure 15. **In-season forecast trade-offs for Summer 5_2 Chinook, between mean percent error (MPE), mean absolute percent error (MAPE) and availability. The top panel presents performance measures for all Summer 5_2 forecasts, colour-coded as follows: dark blue-linear models; light blue-exponential models; dark brown-allometric models; light brown-composite models. The bottom panel focuses on the best performing models, which are labelled according to analysis week, colour-coded as above, and colour-graded with earlier weeks appearing darker and later weeks appearing lighter.**

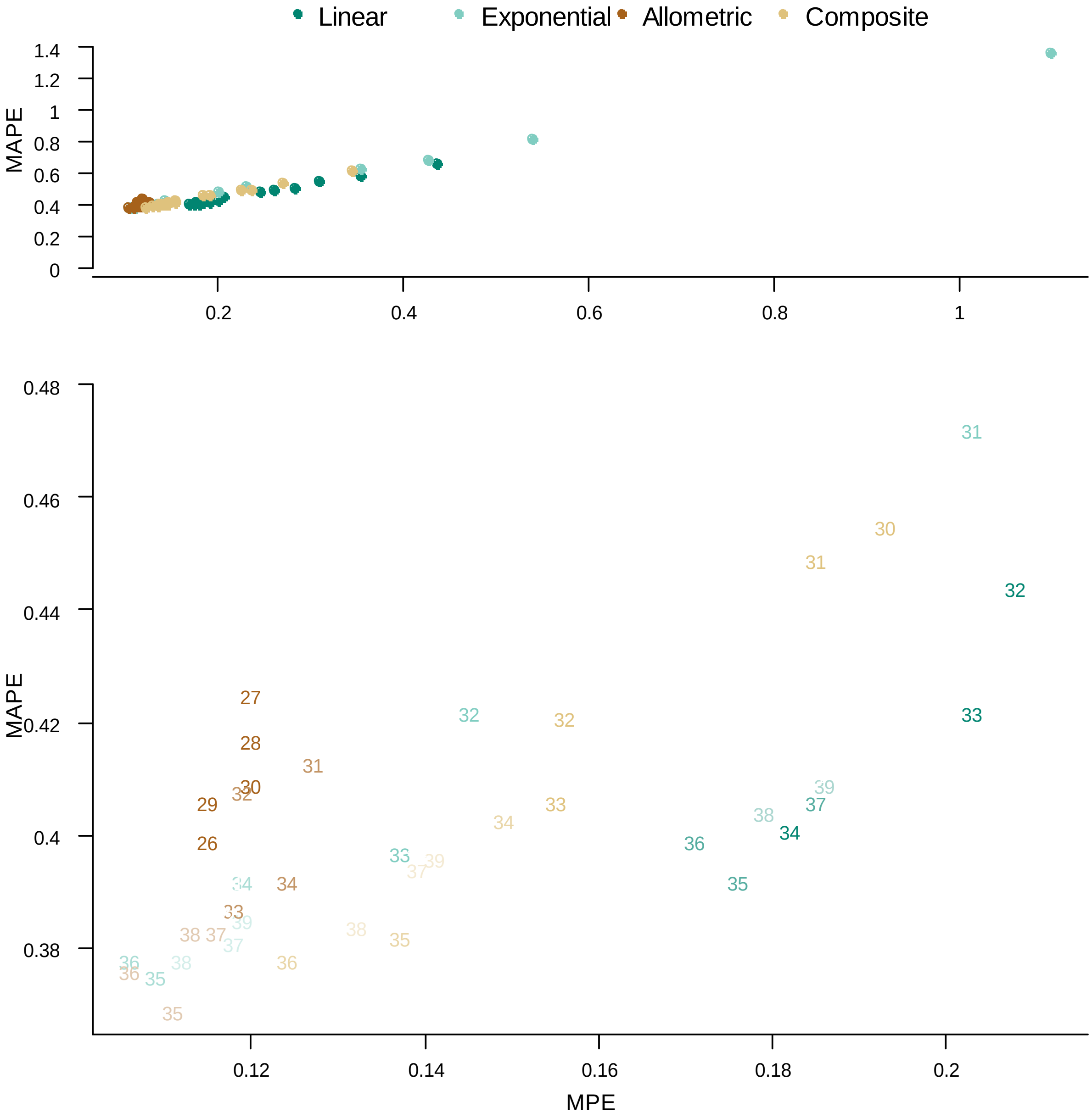


Figure 16. In-season forecast trade-offs for Summer 41 Chinook, between mean percent error (MPE), mean absolute percent error (MAPE) and availability. The top panel presents performance measures for all Summer 41 forecasts, colour-coded as follows: dark blue-linear models; light blue-exponential models; dark brown-allometric models; light brown-composite models. The bottom panel focuses on the best performing models, which are labelled according to analysis week, colour-coded as above, and colour-graded with earlier weeks appearing darker and later weeks appearing lighter.

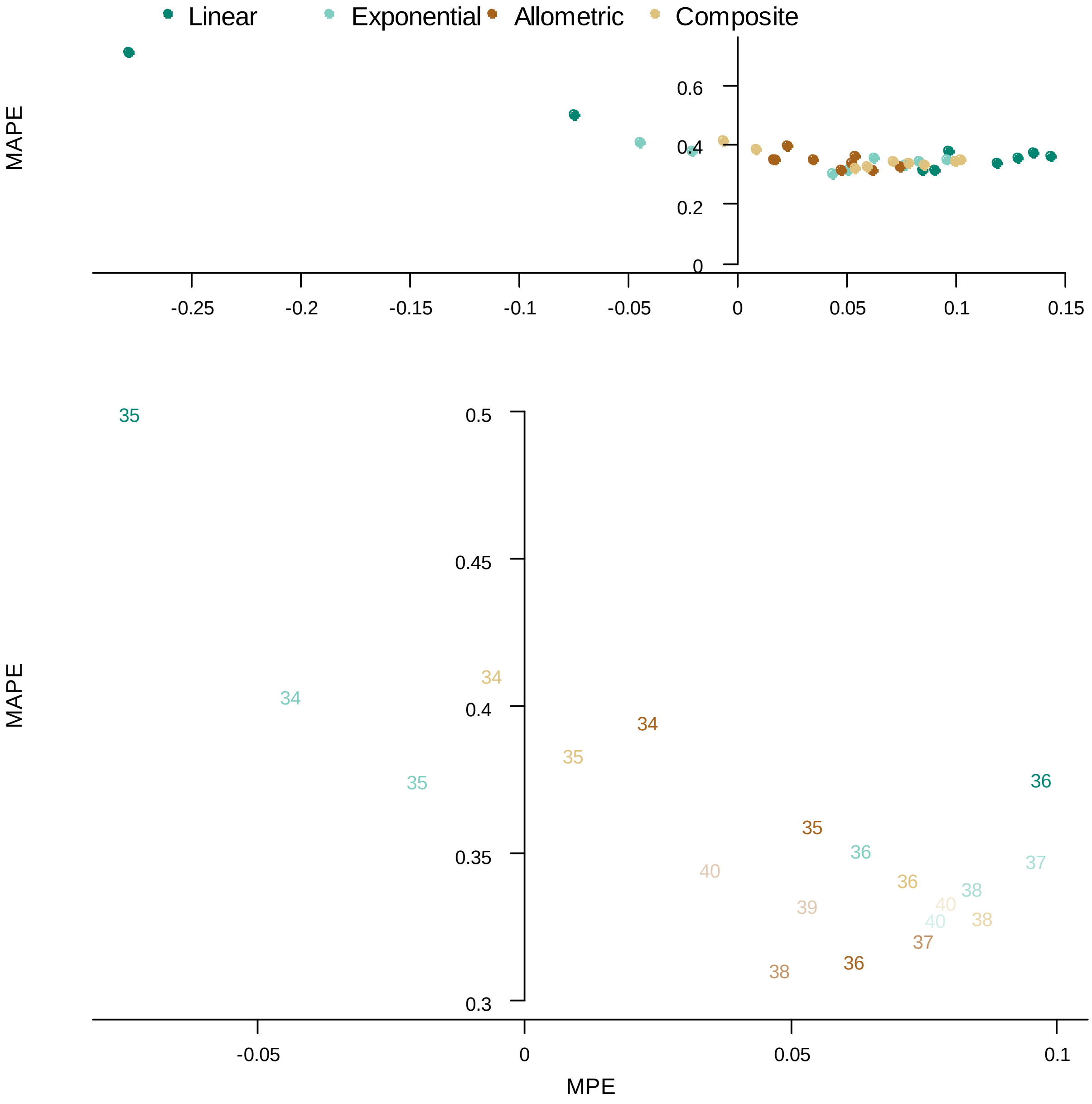


Figure 17. In-season forecast trade-offs for Fall Chinook, between mean percent error (MPE), mean absolute percent error (MAPE) and availability. The top panel presents performance measures for all Fall forecasts, colour-coded as follows: dark blue-linear models; light blue-exponential models; dark brown-allometric models; light brown-composite models. The bottom panel focuses on the best performing models, which are labelled according to analysis week, colour-coded as above, and colour-graded with earlier weeks appearing darker and later weeks appearing lighter.

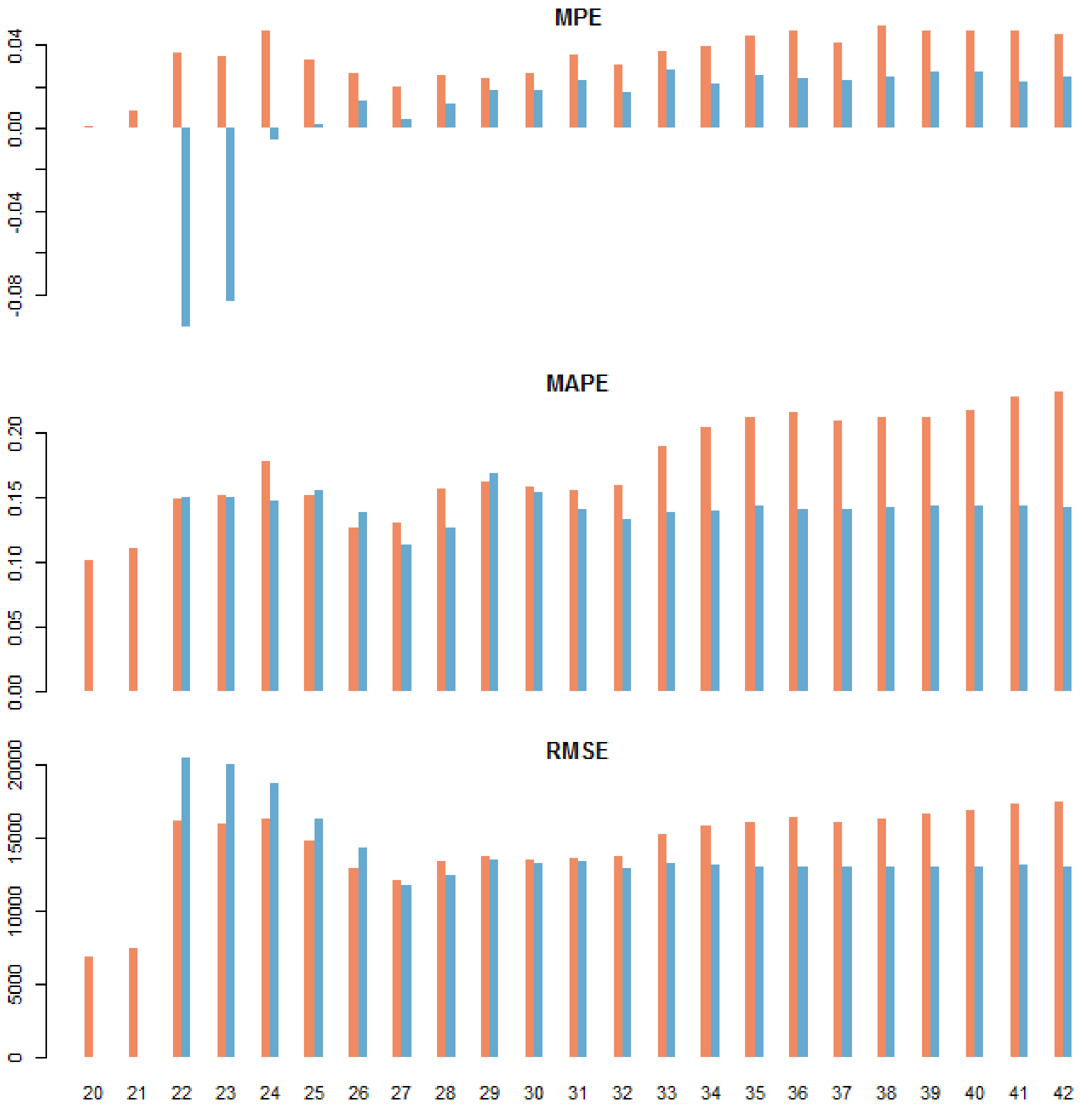


Figure 18. Mean percent error (MPE), mean absolute percent error (MAPE), and root mean squared error (RMSE) of the current in-season Spring and Summer 5_2 forecast model (pink bars), and the allometric model applied to single panel CPUE indices for the Spring 5_2 and Summer 5_2 management units combined (blue bars). Statistical weeks of analysis are indicated on the x-axis.

Appendix A

Cumulative CPUE Indices and Return Data

Table A1. **Cumulative CPUE indices for Spring 4_2 Chinook using all catch data.**

Week	Year									
	2000	2001	2005	2006	2008	2009	2010	2012	2013	2014
23	0.24	0.47	0.03	0.05	0.00	0.01	0.01	0.04	0.00	0.05
24	0.28	0.77	0.03	0.05	0.00	0.03	0.04	0.04	0.00	0.06
25	0.30	0.86	0.04	0.17	0.03	0.04	0.06	0.04	0.00	0.11
26	0.30	0.90	0.06	0.19	0.06	0.08	0.10	0.04	0.00	0.19
27	0.57	0.90	0.13	0.20	0.09	0.23	0.16	0.04	0.01	0.40
28	0.73	0.90	0.16	0.23	0.09	0.33	0.17	0.06	0.03	0.44
29	0.91	0.90	0.16	0.24	0.20	0.39	0.21	0.07	0.03	0.47
30	1.02	0.90	0.16	0.32	0.26	0.54	0.22	0.08	0.05	0.48
31	1.04	1.53	0.16	0.40	0.32	0.68	0.23	0.09	0.05	0.49
32	1.04	2.19	0.16	0.52	0.32	0.79	0.24	0.09	0.06	0.50
33	1.04	2.84	0.16	0.55	0.32	0.87	0.24	0.09	0.06	0.50
34	1.04	3.05	0.16	0.55	0.32	0.96	0.24	0.09	0.06	0.50
35	1.04	3.05	0.16	0.55	0.32	1.00	0.24	0.09	0.06	0.50
36	1.04	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
37	1.04	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
38	1.04	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
39	1.08	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
40	1.08	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
41	1.08	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50
42	1.08	3.05	0.16	0.55	0.32	1.01	0.24	0.09	0.06	0.50

Table A2. **Cumulative CPUE indices for Spring 5_2 Chinook using single panel catch data only.**

Week	Year										
	2000	2001	2005	2006	2008	2009	2010	2011	2012	2013	2014
20	0.13	0.69	0.09	0.14	0.09	0.19	0.08	0.07	0.03	0.02	0.00
21	0.48	1.54	0.12	0.19	0.09	0.19	0.16	0.15	0.03	0.04	0.00
22	0.68	2.77	0.35	0.36	0.15	0.38	0.20	0.15	0.07	0.04	0.07
23	1.04	3.77	0.43	0.56	0.19	0.46	0.22	0.15	0.10	0.04	0.10
24	1.51	4.88	0.46	0.90	0.37	0.56	0.51	0.22	0.12	0.13	0.24
25	2.22	5.04	0.97	1.82	0.77	0.98	1.08	0.28	0.15	0.17	0.61
26	3.76	5.17	1.32	2.27	1.37	2.06	1.67	0.52	0.15	0.29	1.34
27	5.70	5.20	1.85	2.46	1.93	3.18	2.70	0.60	0.24	0.33	2.03
28	6.98	5.23	2.01	2.67	2.12	3.47	3.27	0.60	0.38	0.44	2.23
29	7.78	5.27	2.13	3.00	2.38	3.72	3.50	0.78	0.40	0.49	2.36
30	8.08	6.51	2.36	3.25	2.51	4.13	3.75	0.98	0.44	0.62	2.50
31	8.24	10.64	2.39	3.30	2.63	4.21	3.78	1.13	0.44	0.62	2.50
32	8.24	13.51	2.43	3.32	2.65	4.32	3.78	1.16	0.46	0.62	2.53
33	8.24	14.17	2.43	3.32	2.72	4.33	3.80	1.18	0.48	0.62	2.53
34	8.36	14.40	2.43	3.32	2.72	4.33	3.85	1.18	0.50	0.62	2.53
35	8.36	14.40	2.43	3.32	2.72	4.33	3.85	1.18	0.50	0.62	2.53
36	8.36	14.40	2.43	3.34	2.72	4.33	3.85	1.18	0.51	0.62	2.53
37	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53
38	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53
39	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53
40	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53
41	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53
42	8.36	14.40	2.43	3.36	2.72	4.33	3.85	1.18	0.51	0.62	2.53

Table A3. **Cumulative CPUE indices for Summer 5_2 Chinook using all catch data.**

Week	Year										
	2000	2001	2005	2006	2008	2009	2010	2011	2012	2013	2014
25	0.28	2.12	0.29	0.10	0.05	0.04	0.08	0.00	0.01	0.01	0.07
26	0.45	3.17	0.37	0.15	0.09	0.20	0.17	0.01	0.01	0.02	0.17
27	0.85	3.74	0.61	0.30	0.17	0.61	0.43	0.01	0.03	0.05	0.68
28	1.30	3.86	0.86	0.54	0.33	0.93	0.83	0.03	0.05	0.19	1.08
29	2.37	3.87	1.29	1.09	1.31	1.07	1.08	0.10	0.12	0.30	1.38
30	3.89	3.89	1.98	1.70	1.64	1.87	1.39	0.26	0.21	0.47	2.01
31	5.14	3.92	2.51	2.15	2.23	2.31	1.55	0.60	0.29	0.72	2.47
32	6.76	4.39	3.22	2.68	2.40	2.82	1.86	0.85	0.47	1.08	3.10
33	7.34	5.62	3.43	2.89	2.74	3.05	1.98	1.23	0.68	1.18	3.38
34	7.65	7.00	3.71	3.07	2.94	3.31	2.13	1.42	0.79	1.34	3.52
35	7.76	7.88	3.96	3.09	3.00	3.38	2.16	1.62	0.88	1.37	3.67
36	7.87	8.11	4.20	3.15	3.03	3.43	2.18	1.73	0.88	1.39	3.81
37	7.87	8.28	4.20	3.18	3.03	3.50	2.18	1.82	0.92	1.39	3.81
38	7.87	8.31	4.20	3.18	3.06	3.52	2.18	1.88	0.92	1.41	3.81
39	7.87	8.31	4.20	3.18	3.06	3.52	2.18	1.89	0.92	1.41	3.81
40	7.87	8.31	4.20	3.18	3.06	3.52	2.18	1.89	0.92	1.43	3.81
41	7.87	8.31	4.20	3.18	3.06	3.52	2.18	1.89	0.92	1.43	3.81
42	7.87	8.31	4.20	3.18	3.06	3.52	2.18	1.89	0.92	1.43	3.81

Table A4. **Cumulative CPUE indices for Summer 41 Chinook using all catch data.**

Week	Year										
	2000	2001	2005	2006	2008	2009	2010	2011	2012	2013	2014
26	0.01	1.07	0.01	0.20	0.02	0.04	0.46	0.01	0.00	0.01	0.06
27	0.10	3.62	0.02	0.53	0.05	0.08	0.99	0.04	0.01	0.01	0.26
28	0.27	6.09	0.06	0.77	0.06	0.09	2.20	0.07	0.04	0.06	0.50
29	0.95	7.73	0.14	1.33	0.32	0.17	2.95	0.07	0.05	0.13	0.67
30	1.65	8.12	0.29	2.12	0.59	0.32	3.91	0.13	0.11	0.28	0.99
31	2.26	8.12	0.49	2.78	1.14	0.56	4.25	0.34	0.24	0.51	1.31
32	3.60	8.12	0.83	3.60	1.97	0.86	5.05	0.87	0.66	1.08	1.81
33	4.76	8.35	1.30	4.12	4.41	1.82	5.64	2.16	1.82	1.65	2.26
34	6.48	9.07	2.68	4.62	6.91	3.57	7.36	4.02	2.57	3.51	2.89
35	7.13	11.33	4.95	4.81	10.06	4.93	8.35	6.32	3.67	4.33	4.11
36	7.94	13.56	7.26	4.95	12.21	5.71	8.73	7.44	4.60	4.82	4.62
37	8.90	15.63	7.26	5.21	12.45	6.02	8.91	8.75	4.74	4.90	5.04
38	9.46	16.56	7.26	5.29	12.54	6.18	8.91	9.04	4.78	4.94	5.08
39	9.46	16.92	7.26	5.31	12.61	6.18	8.93	9.07	4.79	4.97	5.10
40	9.46	17.31	7.26	5.31	12.61	6.18	8.93	9.07	4.79	4.97	5.10
41	9.46	17.31	7.26	5.32	12.61	6.18	8.93	9.08	4.79	4.97	5.10
42	9.46	17.41	7.26	5.32	12.61	6.18	8.93	9.08	4.79	4.97	5.10

Table A5. **Cumulative CPUE indices for Fall Chinook using single panel catch data only.**

Week	Year										
	2000	2001	2005	2006	2008	2009	2010	2011	2012	2013	2014
34	0.12	4.71	0.00	0.00	0.13	0.15	0.05	0.03	0.03	0.18	0.04
35	0.12	4.71	0.00	0.02	1.02	0.38	0.05	0.09	0.15	0.37	0.38
36	0.68	4.74	0.13	0.10	3.90	1.32	0.28	0.19	0.61	1.26	1.09
37	2.09	4.90	0.13	0.85	5.57	2.99	1.28	1.06	1.27	1.72	2.09
38	4.31	4.94	0.13	1.12	6.32	4.58	1.80	2.63	1.64	2.30	2.46
39	5.53	4.96	0.13	1.37	6.89	5.31	3.15	3.53	2.15	2.90	2.75
40	6.86	4.96	0.13	1.37	6.89	6.03	4.27	5.97	2.24	3.14	2.95
41	7.46	5.00	0.13	1.45	6.89	6.32	5.57	9.56	2.34	3.25	3.35
42	7.69	5.00	0.13	1.47	6.89	6.39	5.84	10.09	2.53	3.31	3.49

Table A6. Reconstructed annual returns for each management unit.

Year	Spring 4_2	Spring 5_2	Summer 5_2	Summer 4_1	Fall
2000	28599	40669	33787	68534	157554
2001	31128	47720	39639	116020	193666
2002	35570	54704	45034	157627	166617
2003	40816	71286	55960	125385	310530
2004	39324	54290	51514	92774	206471
2005	15363	35636	31357	131457	134750
2006	19654	34580	33640	228414	120499
2008	17830	27137	25540	151591	89119
2009	4279	43481	29551	123300	98207
2010	13378	26320	24855	214563	194866
2011	7923	19776	27667	187124	184944
2012	15489	17811	17029	75538	73343
2013	7492	23521	18458	144689	116791
2014	21553	50655	43553	115431	123187

Appendix B

Parameter Estimates by Management Unit, Model Form and Analysis Week

Table B1. Model parameter estimates for Spring 4_2 Chinook (all data).

Analysis Week	Linear Model			Exponential Model			Allometric Model		
	α	β	σ	α	β	σ	α	β	σ
23	14650	25250	6488	9.49	1.36	0.59	10.63	0.35	0.52
24	14440	22540	5885	9.49	1.19	0.54	10.50	0.33	0.50
25	13850	21970	6079	9.46	1.15	0.55	10.37	0.33	0.54
26	10965	23845	5635	9.29	1.27	0.54	10.10	0.25	0.57
27	10570	21795	5982	9.28	1.11	0.56	10.07	0.27	0.59
28	10310	20200	6032	9.27	1.03	0.56	10.04	0.29	0.58
29	10590	17200	6722	9.31	0.81	0.60	9.97	0.26	0.60
30	11310	12330	6643	9.35	0.57	0.59	9.90	0.24	0.60
31	12390	8628	6889	9.40	0.40	0.60	9.86	0.22	0.61
32	13100	6465	7107	9.43	0.30	0.61	9.83	0.20	0.61
33	13400	5844	7298	9.45	0.27	0.62	9.82	0.19	0.62
34	13470	5699	7337	9.45	0.25	0.62	9.82	0.19	0.62
35	13410	5786	7349	9.45	0.26	0.62	9.82	0.18	0.62
36	13560	5691	7367	9.46	0.25	0.62	9.81	0.19	0.62
37	13440	5676	7301	9.45	0.25	0.61	9.82	0.18	0.62
38	13470	5693	7319	9.46	0.25	0.62	9.81	0.19	0.62
39	13455	5740	7281	9.46	0.26	0.61	9.81	0.19	0.62
40	13430	5742	7314	9.45	0.26	0.62	9.81	0.19	0.62
41	13470	5704	7286	9.46	0.25	0.61	9.81	0.19	0.62
42	12840	5655	9238	9.49	0.02	0.76	9.61	0.10	0.75

Table B2. **Model parameter estimates for Spring 5_2 Chinook (single panel data only).**

Analysis	Linear Model			Exponential Model			Allometric Model		
Week	α	β	σ	α	β	σ	α	β	σ
20	18090	125900	4882	9.89	3.96	0.19	11.16	0.34	0.21
21	23520	38060	7285	10.06	1.17	0.27	10.84	0.27	0.23
22	28150	14450	10315	10.20	0.45	0.33	10.65	0.19	0.32
23	29040	7737	10416	10.23	0.24	0.34	10.59	0.18	0.32
24	28830	5687	10397	10.22	0.18	0.33	10.53	0.23	0.29
25	27290	4845	10020	10.17	0.15	0.32	10.42	0.25	0.26
26	23790	5337	8855	10.05	0.17	0.28	10.31	0.28	0.23
27	22700	4490	8678	10.01	0.15	0.27	10.22	0.28	0.23
28	23570	3691	9309	10.04	0.12	0.29	10.17	0.29	0.23
29	23990	3263	9617	10.05	0.11	0.30	10.15	0.30	0.24
30	23580	3204	9566	10.03	0.11	0.29	10.10	0.31	0.24
31	23470	3062	9450	10.03	0.10	0.29	10.10	0.31	0.25
32	24820	2355	9255	10.09	0.08	0.29	10.09	0.29	0.24
33	25910	1901	9496	10.12	0.06	0.30	10.09	0.28	0.24
34	26200	1784	9616	10.13	0.06	0.31	10.09	0.28	0.25
35	26380	1746	9617	10.14	0.05	0.31	10.09	0.28	0.25
36	26355	1746	9637	10.14	0.05	0.31	10.09	0.28	0.25
37	26360	1741	9542	10.14	0.05	0.31	10.09	0.28	0.25
38	26400	1749	9618	10.14	0.05	0.31	10.09	0.28	0.25
39	26320	1758	9618	10.14	0.06	0.31	10.09	0.28	0.25
40	26350	1764	9626	10.14	0.06	0.31	10.09	0.28	0.25
41	26420	1756	9628	10.14	0.06	0.31	10.09	0.28	0.25
42	26330	1745	9574	10.14	0.05	0.31	10.09	0.28	0.25

Table B3. Model parameter estimates for Summer 5_2 Chinook (all data).

Analysis	Linear Model			Exponential Model			Allometric Model		
Week	α	β	σ	α	β	σ	α	β	σ
25	27840	6150	8283	10.20	0.21	0.31	10.62	0.15	0.23
26	27740	4270	7779	10.20	0.14	0.29	10.53	0.13	0.22
27	26570	4428	7230	10.16	0.15	0.27	10.44	0.13	0.22
28	25070	4894	6851	10.10	0.17	0.26	10.36	0.14	0.23
29	23060	5095	6507	10.03	0.18	0.24	10.29	0.18	0.23
30	21420	4586	6131	9.96	0.17	0.22	10.21	0.22	0.21
31	21060	3870	6414	9.94	0.14	0.23	10.12	0.27	0.19
32	21370	3042	6647	9.96	0.11	0.24	10.03	0.30	0.20
33	21020	2810	6502	9.94	0.10	0.23	9.94	0.34	0.18
34	21070	2529	6453	9.95	0.09	0.23	9.91	0.35	0.19
35	21060	2416	6388	9.95	0.09	0.23	9.88	0.36	0.18
36	20920	2377	6280	9.95	0.09	0.23	9.87	0.36	0.18
37	20805	2397	6272	9.94	0.09	0.23	9.85	0.37	0.17
38	20850	2367	6306	9.94	0.09	0.23	9.85	0.37	0.18
39	20810	2357	6277	9.94	0.09	0.23	9.85	0.37	0.17
40	20855	2383	6318	9.94	0.09	0.23	9.85	0.37	0.18
41	20910	2347	6281	9.94	0.08	0.23	9.85	0.37	0.17
42	20940	2362	6294	9.95	0.09	0.23	9.85	0.37	0.18

Table B4. Model parameter estimates for Summer 41 Chinook (all data).

Analysis Week	Linear Model			Exponential Model			Allometric Model		
	α	β	σ	α	β	σ	α	β	σ
26	146400	7834	54433	11.84	0.06	0.39	12.04	0.06	0.38
27	141000	1078	56201	11.79	0.02	0.42	11.93	0.06	0.40
28	141000	1096	55973	11.79	0.01	0.42	11.87	0.05	0.41
29	140100	592	56639	11.78	0.01	0.42	11.83	0.04	0.42
30	138000	1965	56196	11.77	0.01	0.42	11.81	0.05	0.42
31	136400	2516	56187	11.76	0.02	0.42	11.79	0.07	0.42
32	134200	2774	55776	11.76	0.01	0.42	11.75	0.07	0.42
33	132900	2627	55651	11.76	0.01	0.42	11.72	0.07	0.42
34	124950	3442	55906	11.70	0.02	0.42	11.55	0.17	0.42
35	126800	2374	55691	11.67	0.02	0.42	11.44	0.20	0.41
36	141800	41	56409	11.76	0.01	0.42	11.68	0.06	0.42
37	143900	-216	56679	11.78	0.00	0.42	11.72	0.04	0.42
38	146400	-669	56391	11.80	0.00	0.42	11.74	0.03	0.42
39	146800	-678	56356	11.80	0.00	0.42	11.75	0.02	0.42
40	145100	-435	56387	11.79	0.00	0.42	11.69	0.05	0.42
41	147600	-706	56471	11.81	0.00	0.42	11.75	0.02	0.42
42	146000	-626	56303	11.80	0.00	0.42	11.72	0.03	0.42

Table B5. Model parameter estimates for Fall Chinook (single panel data only).

Analysis Week	Linear Model			Exponential Model			Allometric Model		
	α	β	σ	α	β	σ	α	β	σ
34	128700	13580	47244	11.71	0.10	0.37	11.91	0.06	0.39
35	127200	10875	46422	11.71	0.07	0.36	11.75	-0.01	0.38
36	134200	622	46309	11.77	0.00	0.36	11.75	-0.05	0.35
37	139900	-2205	46114	11.82	-0.02	0.36	11.78	-0.03	0.36
38	137050	-681	46503	11.80	-0.01	0.36	11.77	0.00	0.36
39	133800	475	46249	11.78	0.00	0.36	11.76	0.00	0.36
40	119200	3842	45133	11.67	0.02	0.35	11.74	0.03	0.36
41	108900	5606	42988	11.59	0.04	0.34	11.72	0.04	0.35
42	108600	5553	42930	11.59	0.04	0.34	11.72	0.04	0.36

Appendix C

Model Fit by Management Unit and Model Type

Spring 4_2 Chinook

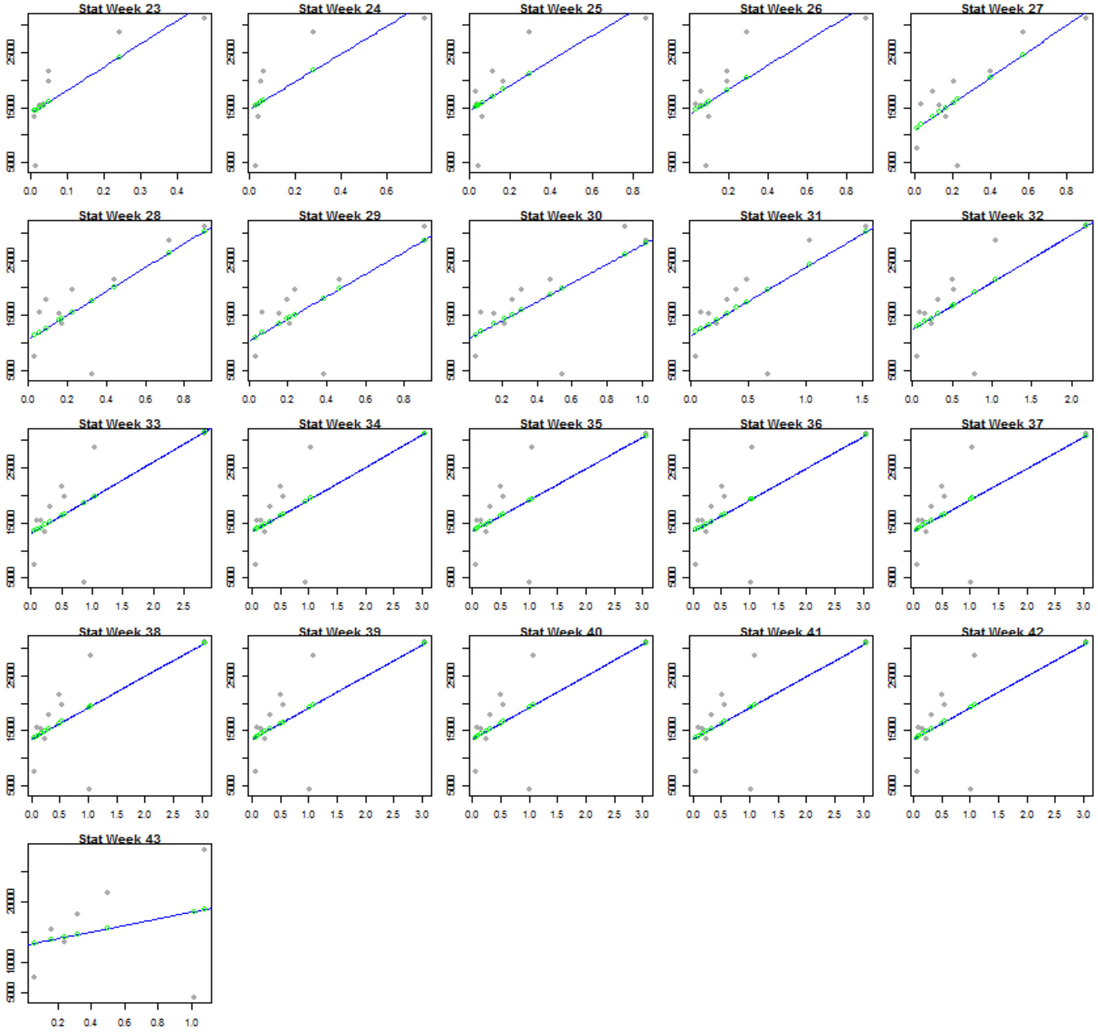


Figure C1. **Cumulative CPUE (all data) (x-axes) and returns (y-axes) of Spring 4_2 Chinook (grey points) with fitted linear model (blue line) and predicted values (green points). Labels indicate analysis week.**

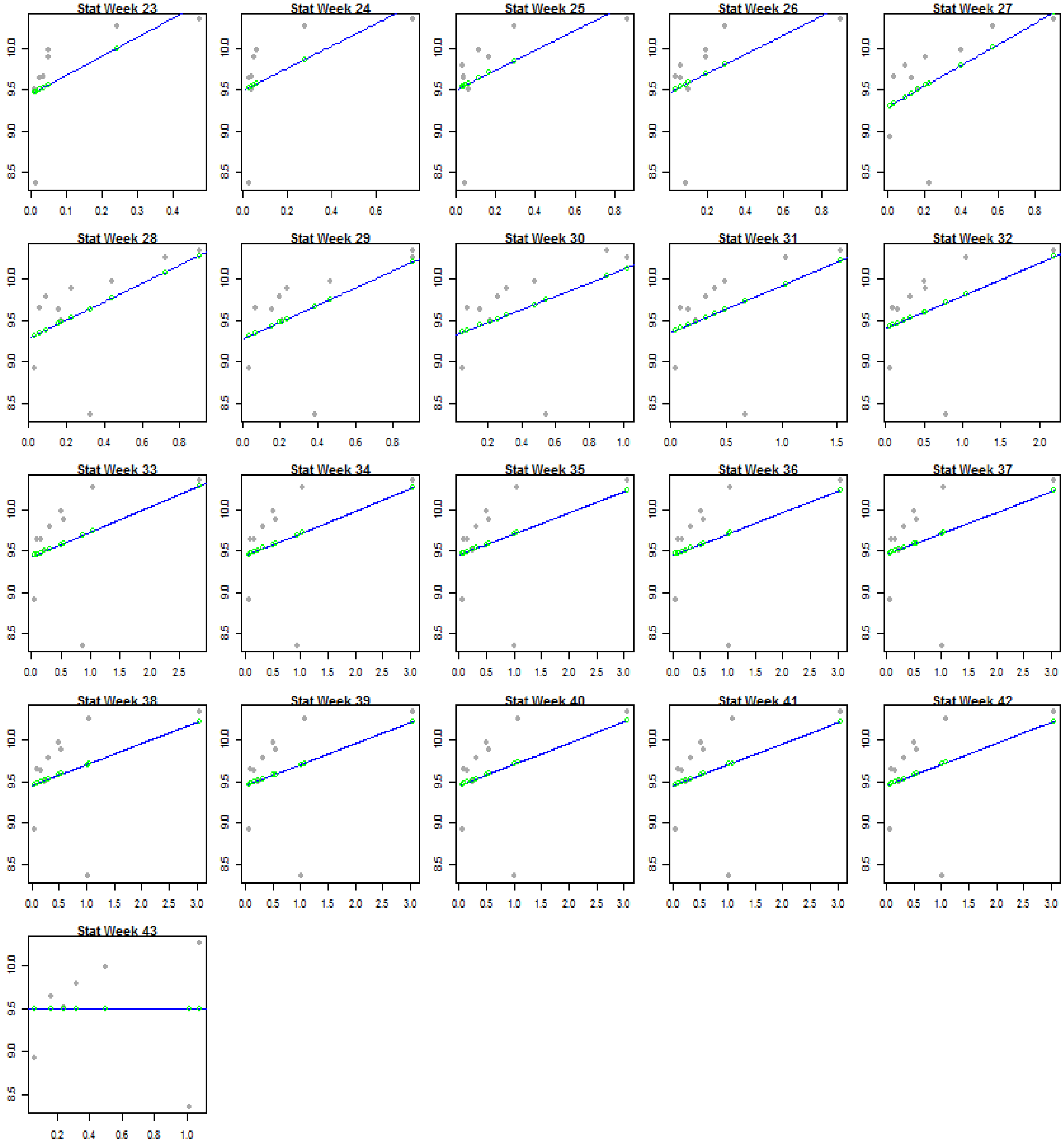


Figure C2. Cumulative CPUE (all data) (x-axes) and log transformed returns of Spring 4_2 Chinook (grey points) with fitted exponential model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

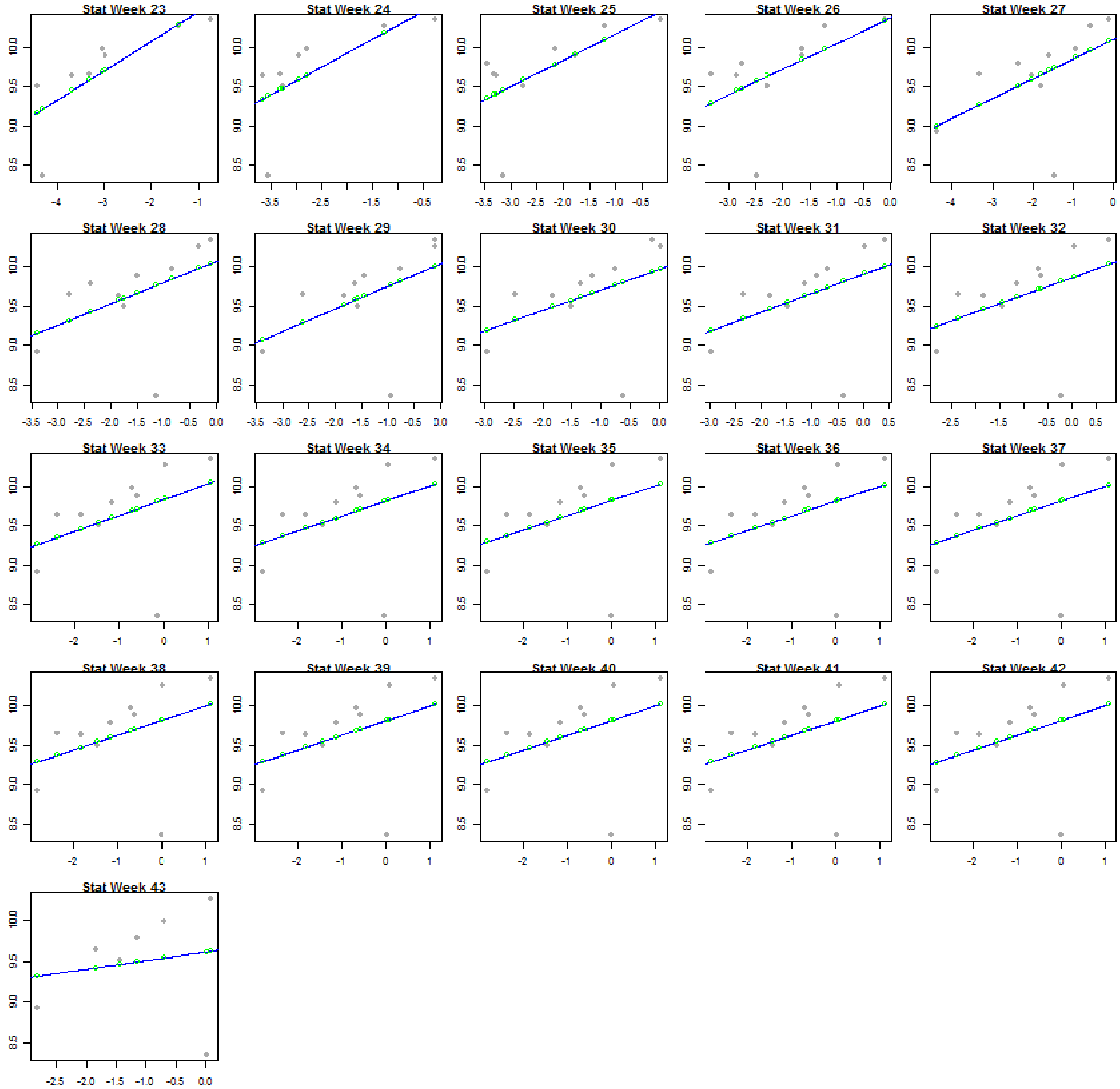


Figure C3. Log transformed cumulative CPUE (all data) (x-axes) and log transformed returns of Spring 4_2 Chinook (grey points) with fitted allometric model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

Spring 5_2 Chinook

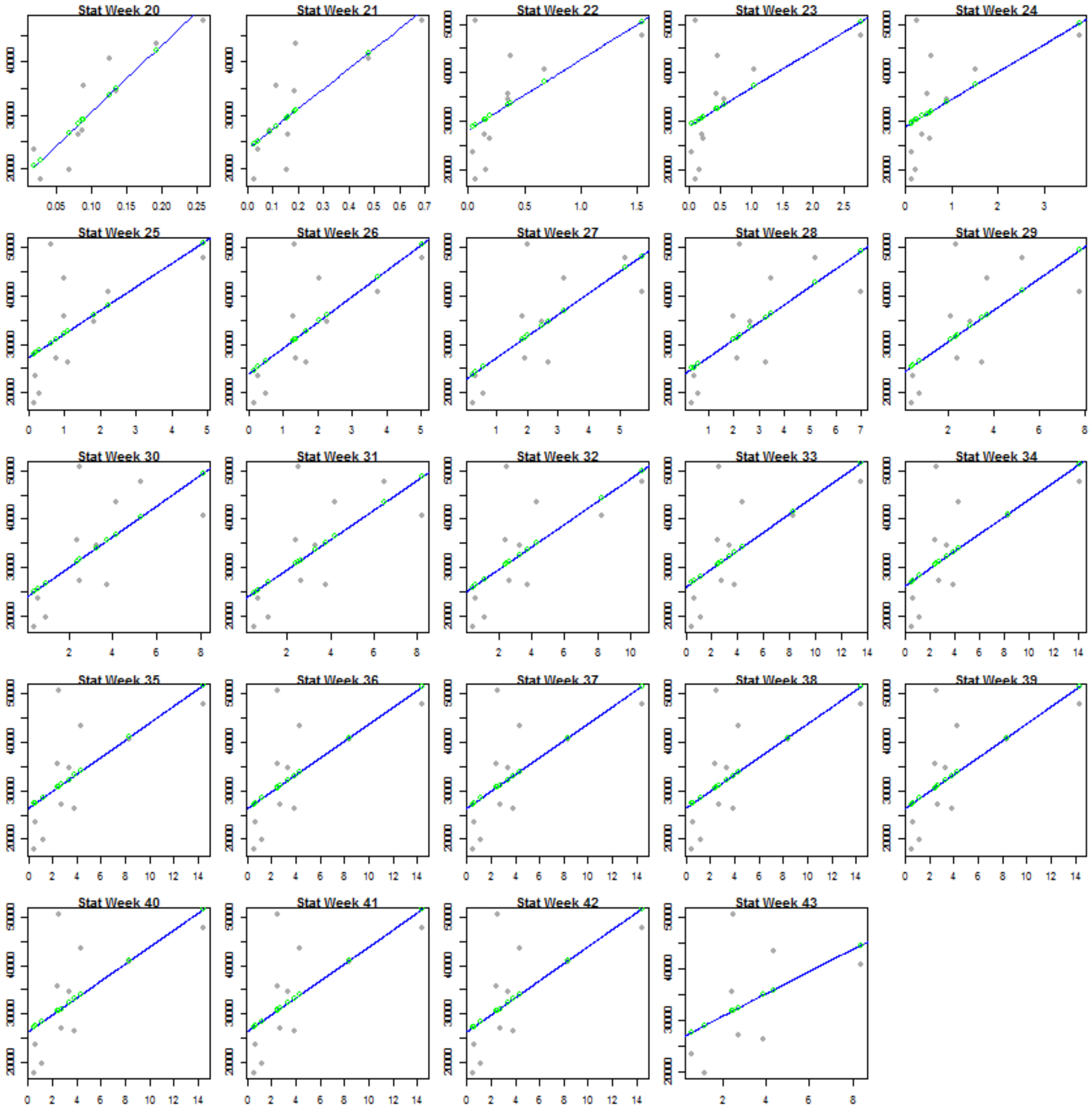


Figure C4. **Cumulative CPUE (single panel data only) (x-axes) and returns (y-axes) of Spring 5_2 Chinook (grey points) with fitted linear model (blue line) and predicted values (green points). Labels indicate analysis week.**

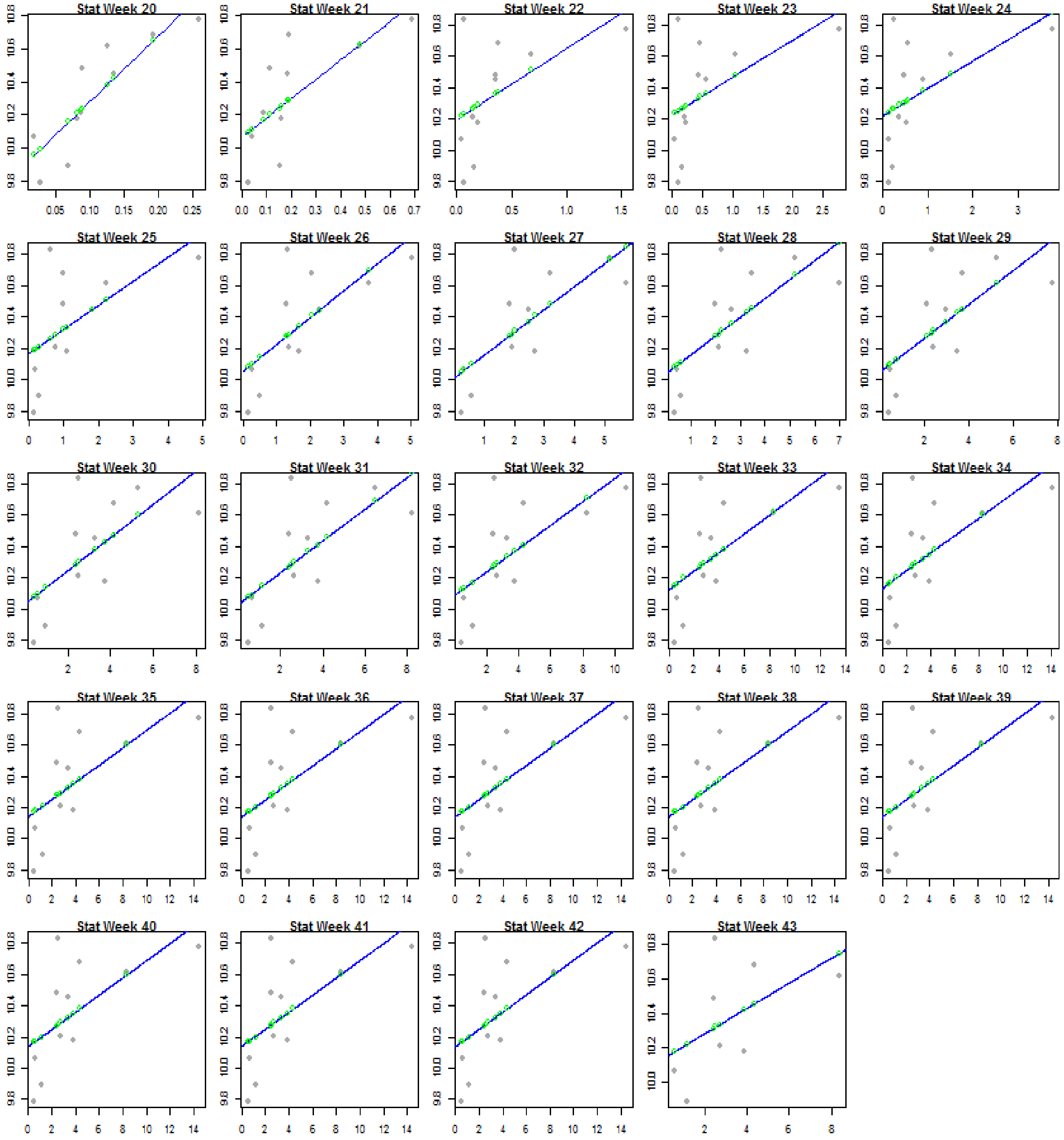


Figure C5. Cumulative CPUE (single panel data only) (x-axes) and log transformed returns of Spring 5_2 Chinook (grey points) with fitted exponential model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

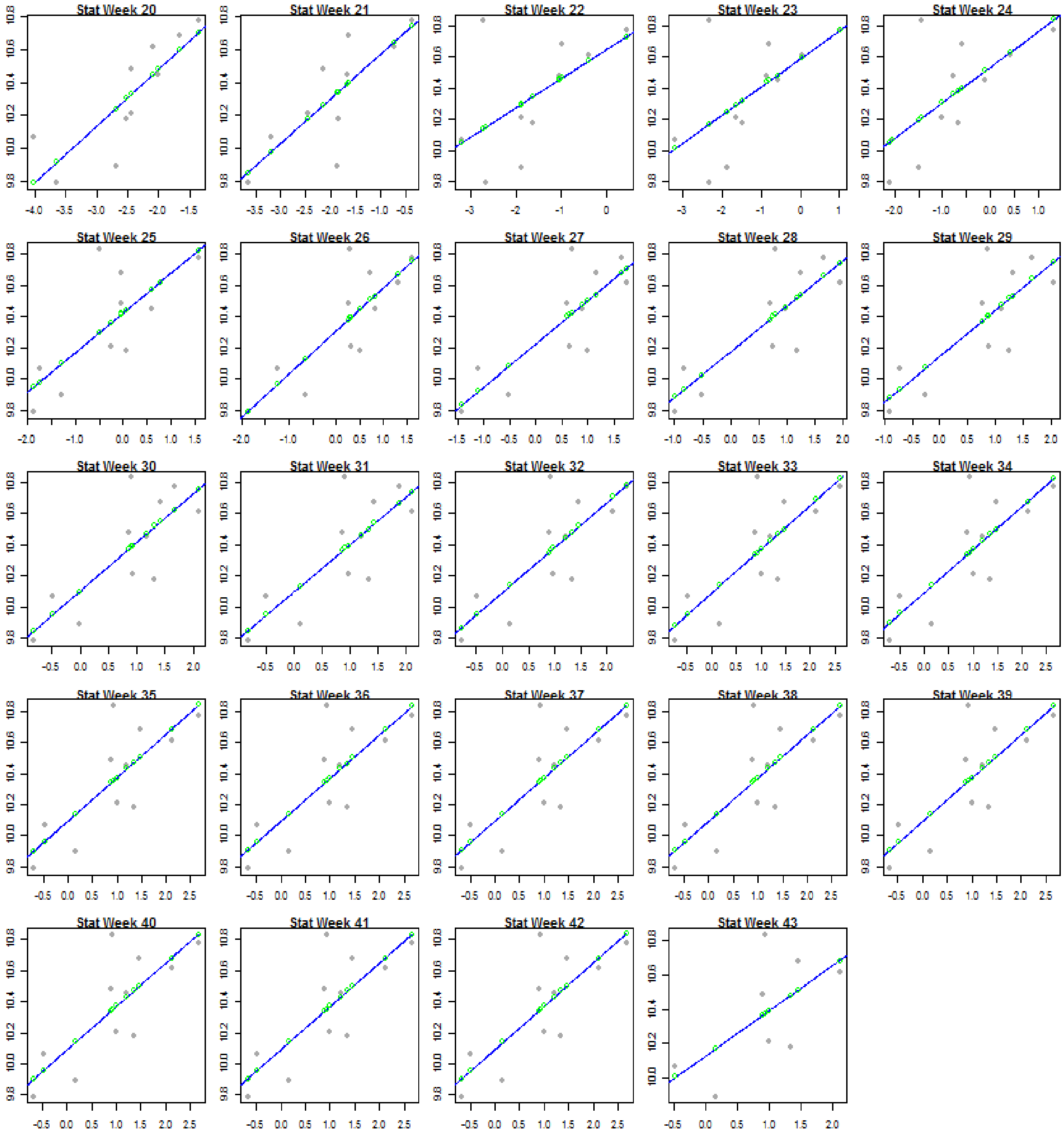


Figure C6. Log transformed cumulative CPUE (single panel data only) (x-axes) and log transformed returns of Spring 5_2 Chinook (grey points) with fitted allometric model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

Summer 5_2 Chinook

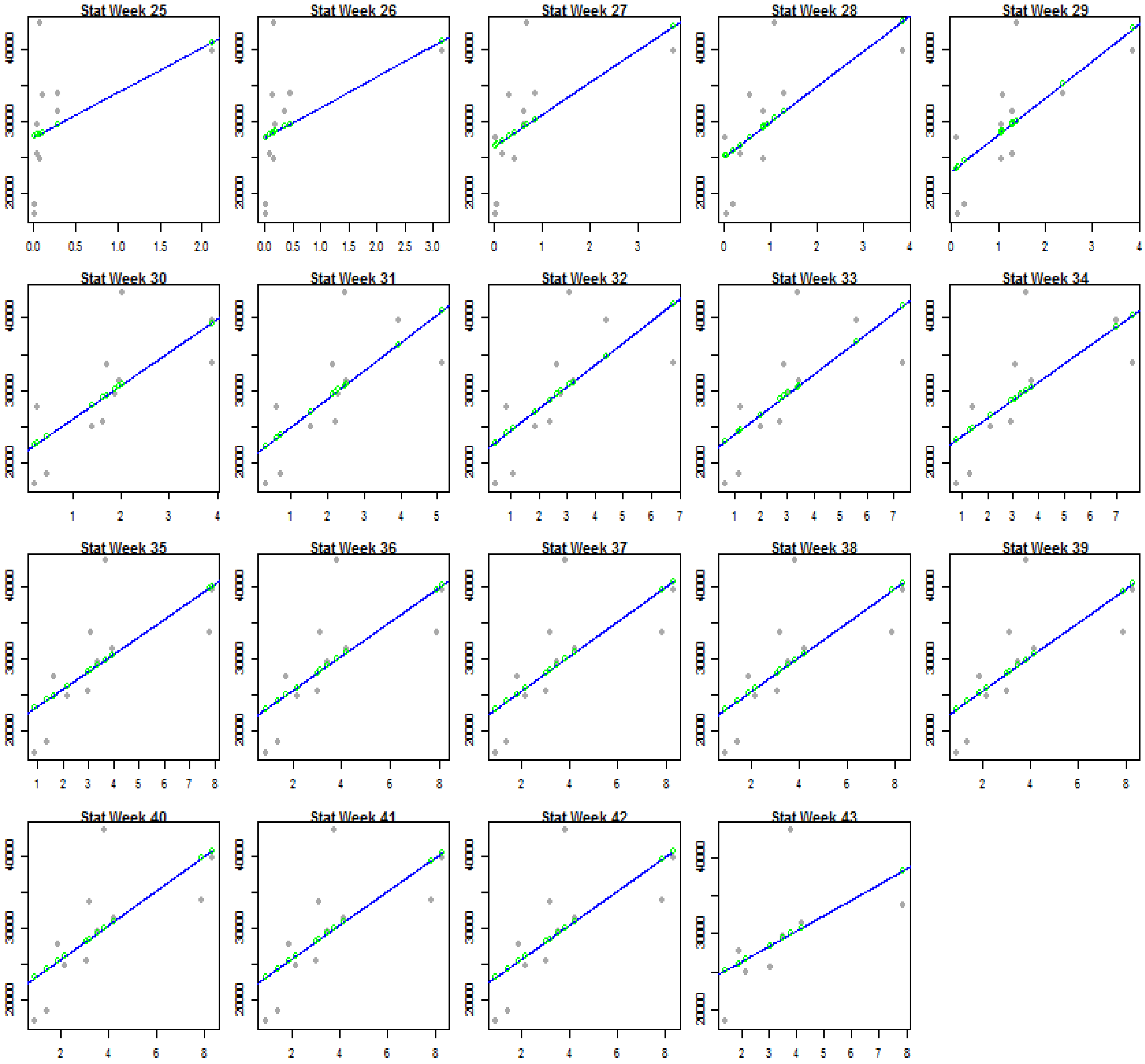


Figure C7. Cumulative CPUE (all data) (x-axes) and returns of Summer 5_2 Chinook (grey points) with fitted linear model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

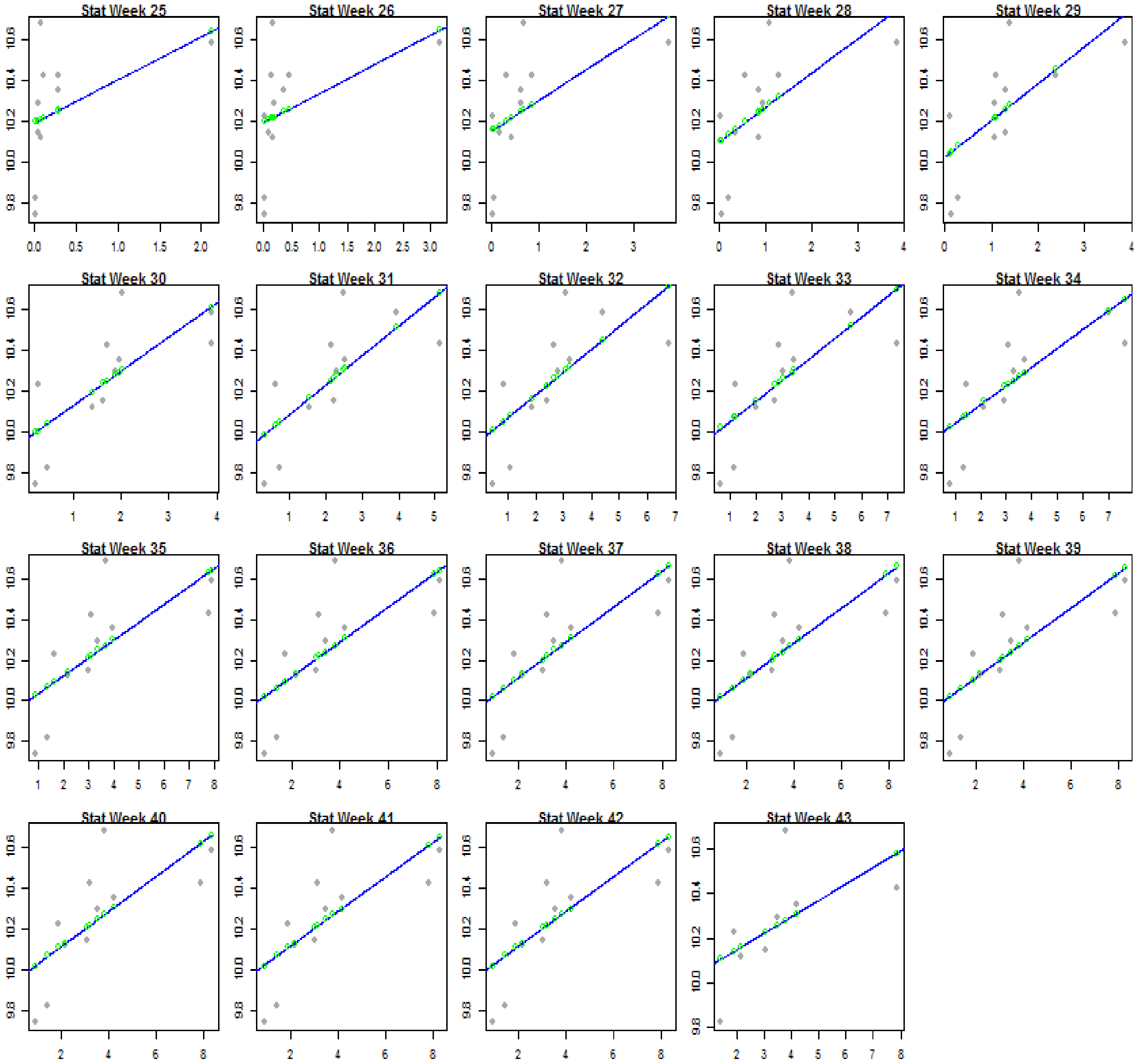


Figure C8. Cumulative CPUE (all data) (x-axes) and log transformed returns of Summer 5_2 Chinook (grey points) with fitted exponential model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

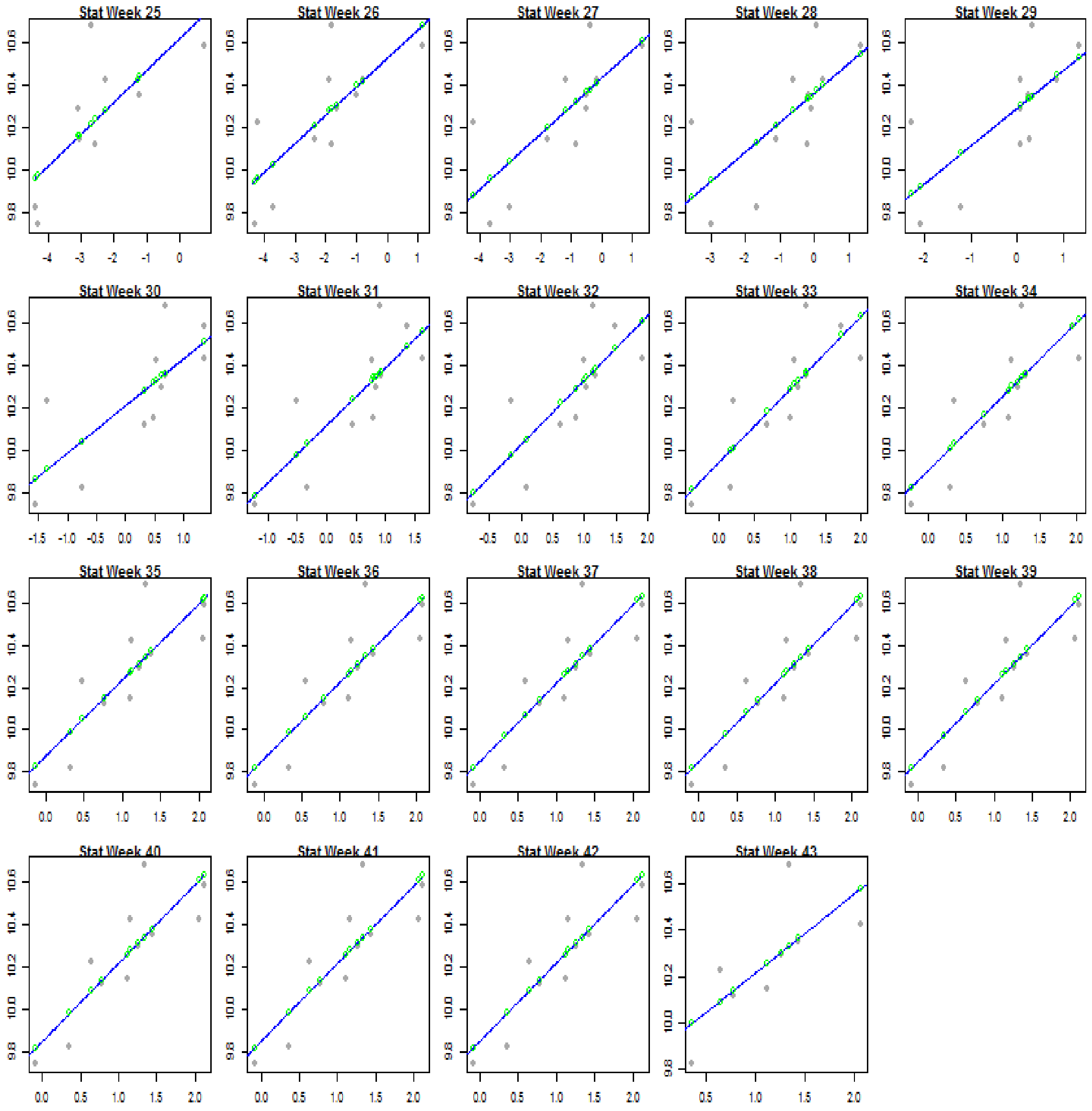


Figure C9. Log transformed cumulative CPUE (all data) (x-axes) and log transformed returns of Summer 5_2 Chinook (grey points) with fitted allometric model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

Summer 4_1 Chinook

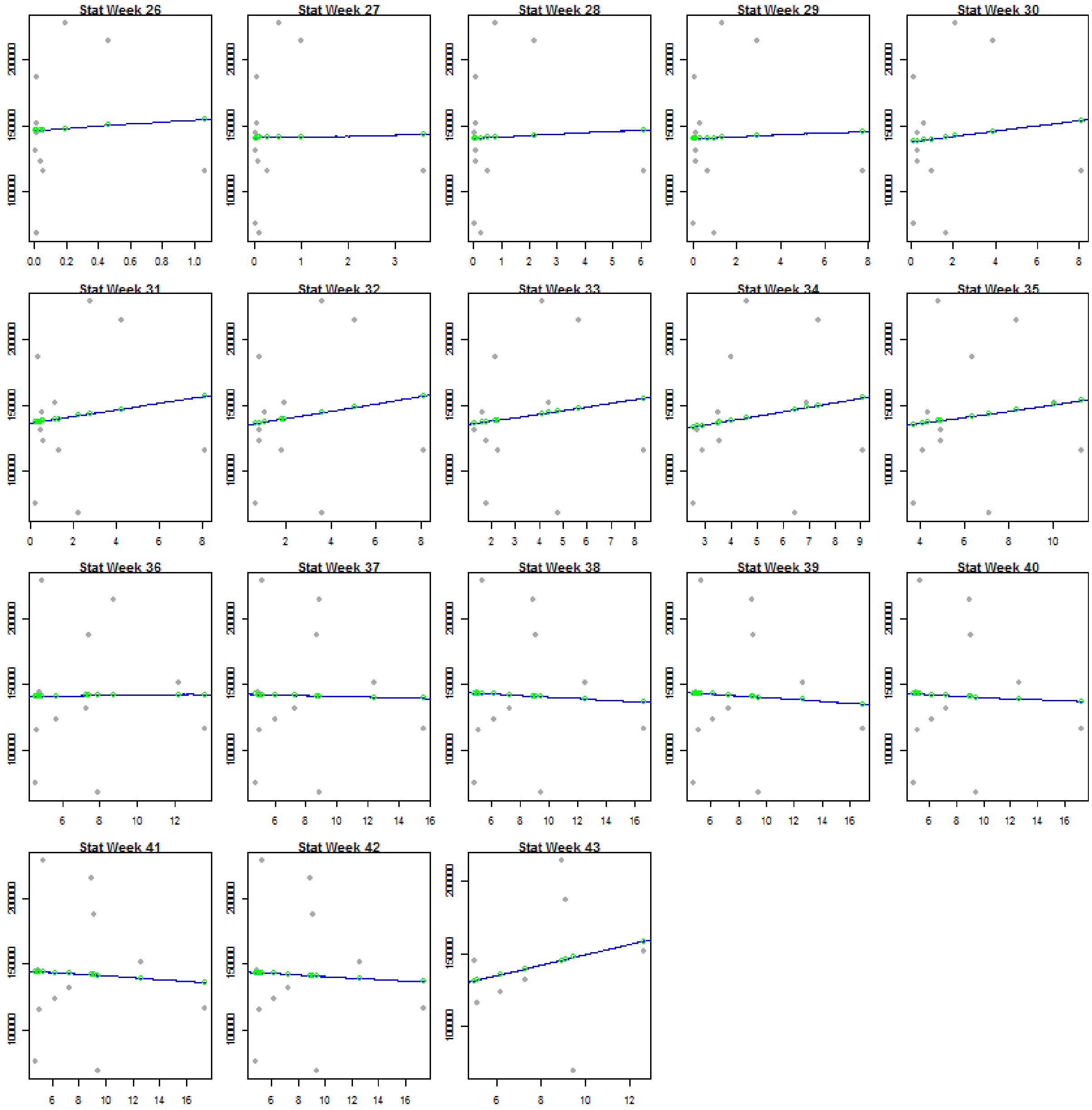
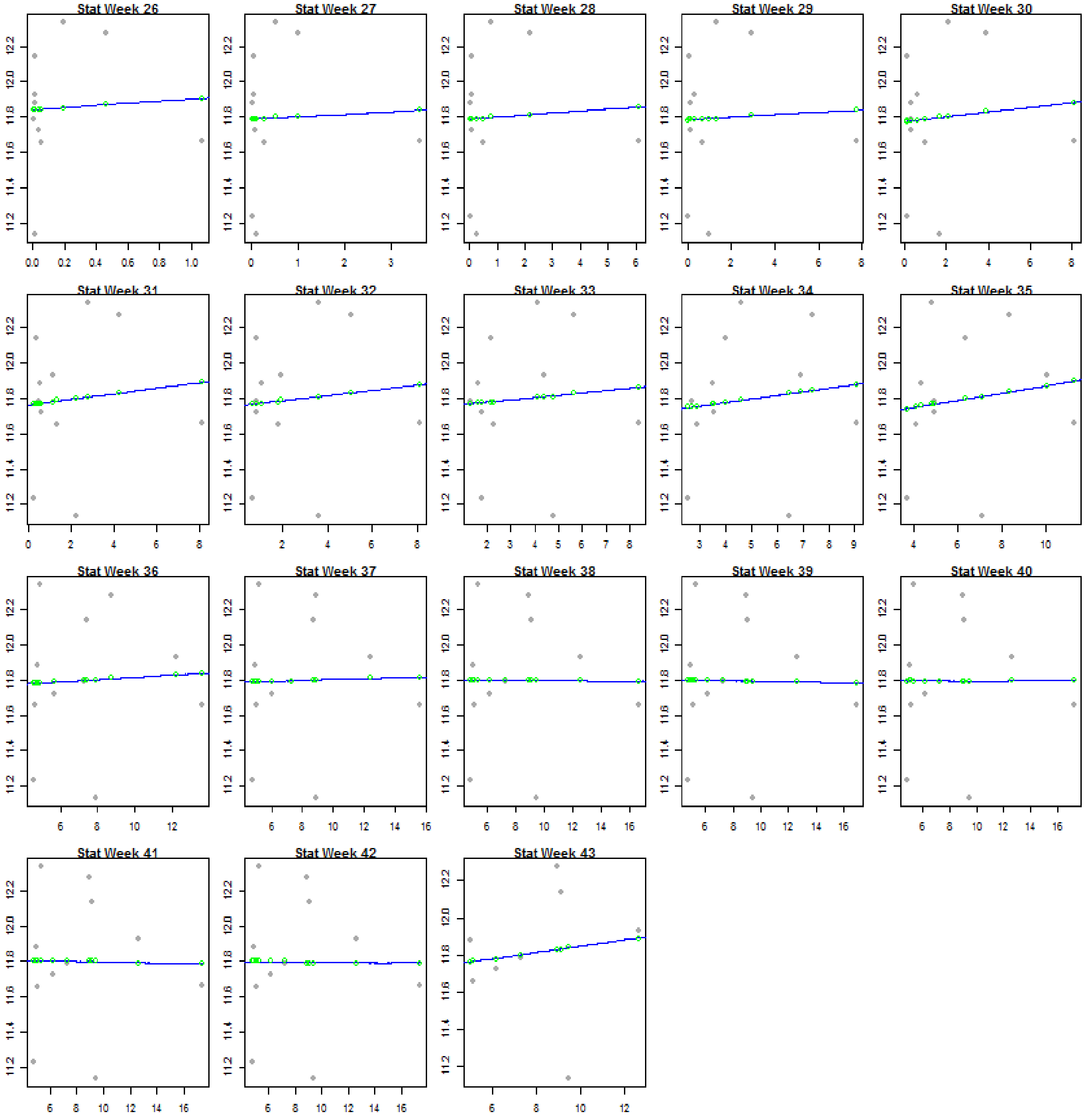


Figure C10. Cumulative CPUE (all data) (x-axes) and returns of Summer 4_1 Chinook (grey points) with fitted linear model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.



Stat Week 26
Stat Week 27
Stat Week 28
Stat Week 29
Stat Week 30
Stat Week 31
Stat Week 32
Stat Week 33
Stat Week 34
Stat Week 35
Stat Week 36
Stat Week 37
Stat Week 38
Stat Week 39
Stat Week 40
Stat Week 41
Stat Week 42
Stat Week 43

Figure C11. **Cumulative CPUE (all data) (x-axes) and log transformed returns of Summer 4$_1$ Chinook (grey points) with fitted exponential model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.**

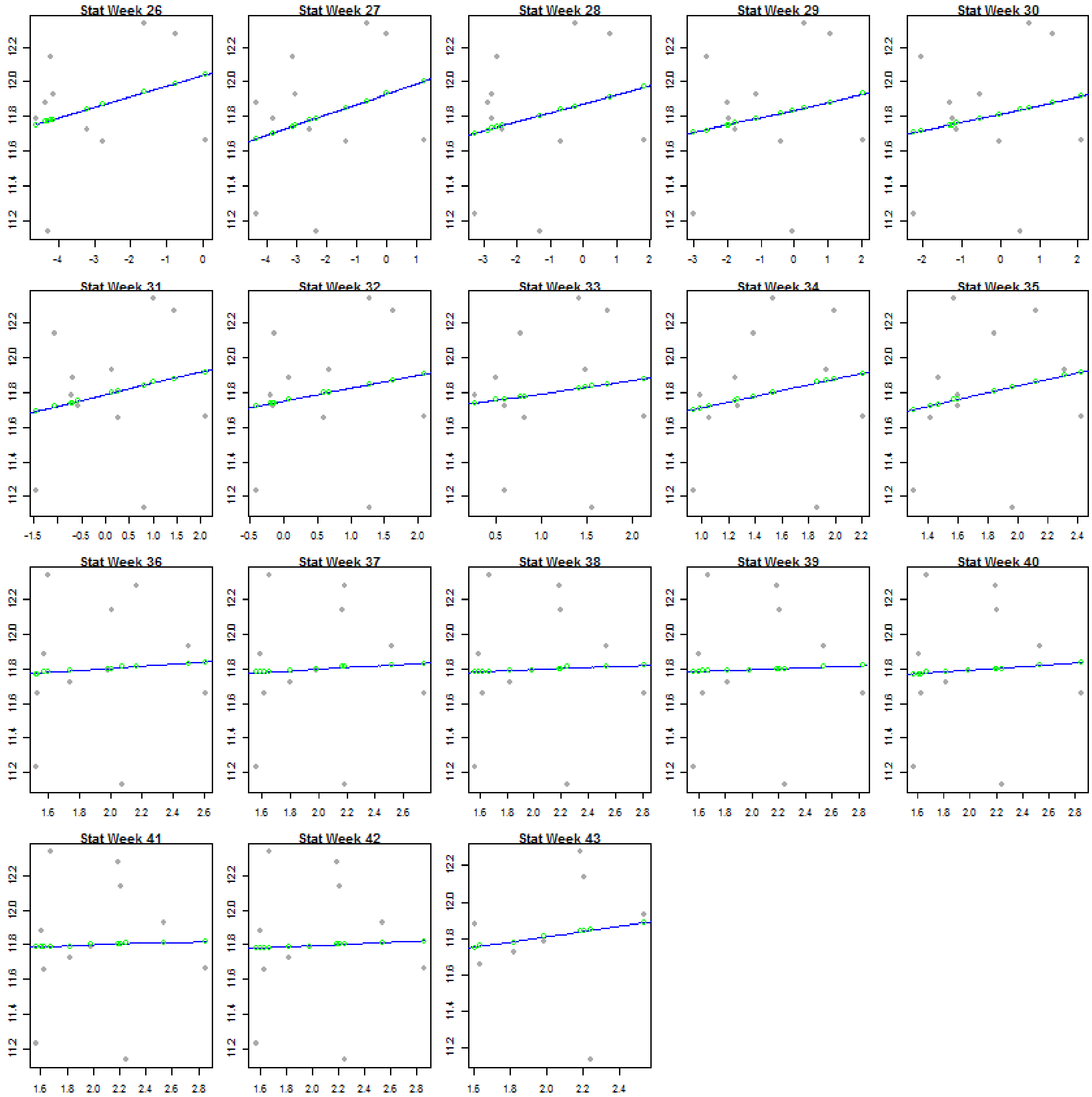


Figure C12. Log transformed cumulative CPUE (all data) (x-axes) and log transformed returns of Summer 4_1 Chinook (grey points) with fitted allometric model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

Fall Chinook

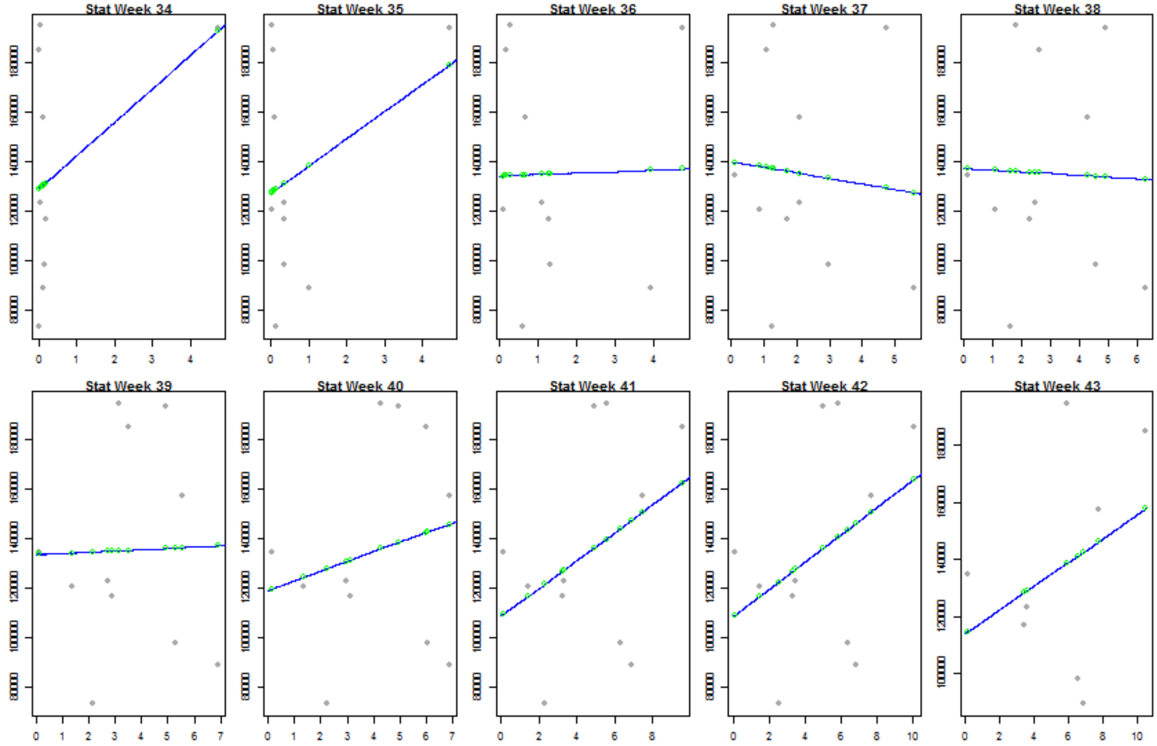


Figure C13. Cumulative CPUE (single panel data only) (x-axes) and returns (y-axes) of Fall Chinook (grey points) with fitted linear model (blue line) and predicted values (green points). Labels indicate analysis week.

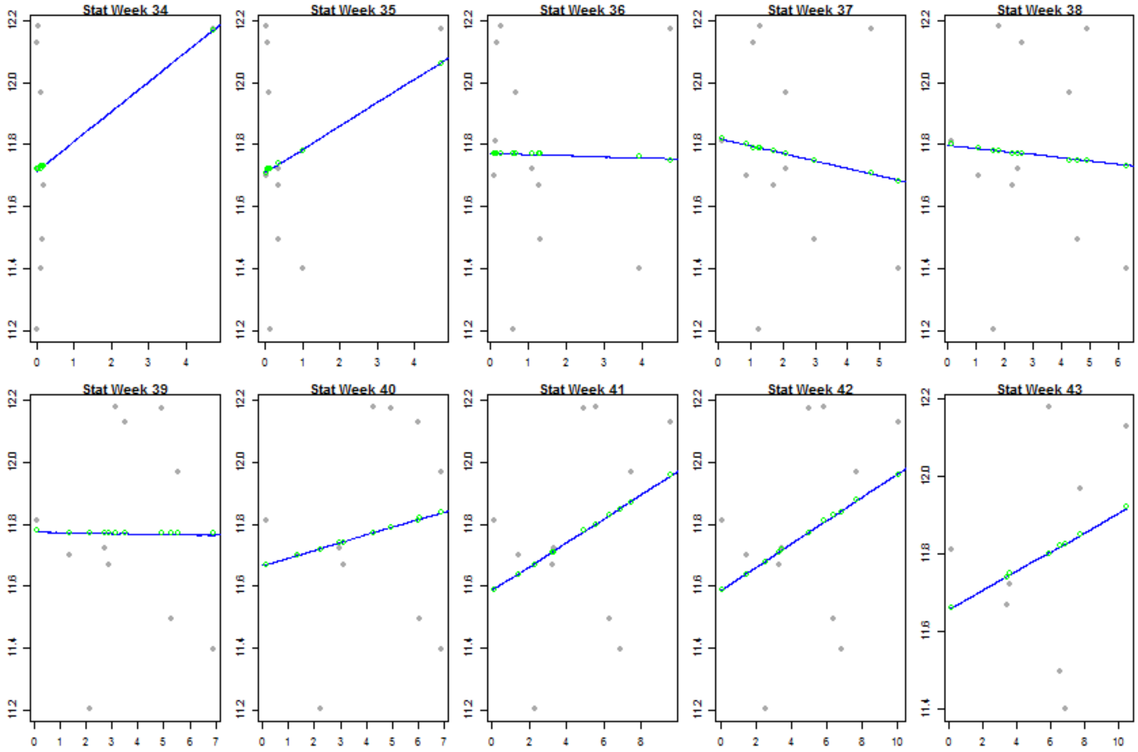


Figure C14. Cumulative CPUE (single panel data only) (x-axes) and log transformed returns of Fall Chinook (grey points) with fitted exponential model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

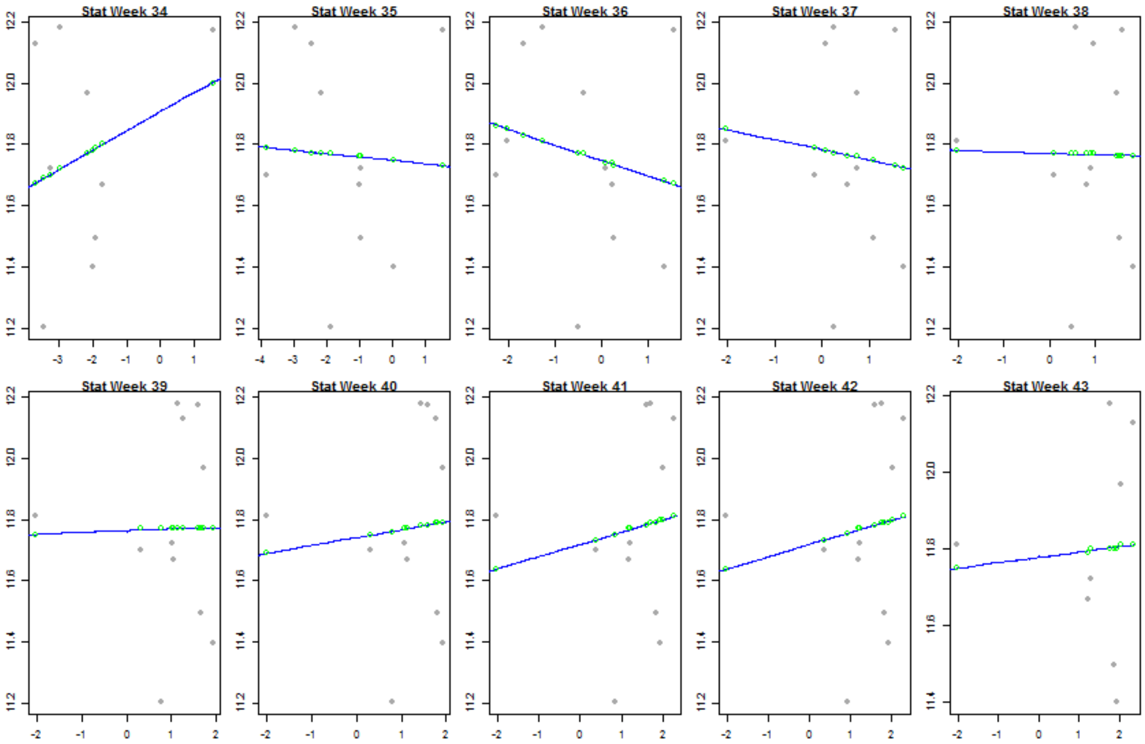


Figure C15. Log transformed cumulative CPUE (single panel data only) (x-axes) and log transformed returns of Fall Chinook (grey points) with fitted allometric model (blue line) and predicted values (green points). Labels indicate statistical week of model fit.

Appendix D

Forecasts by Management Unit and Model Type Produced during Cross-validation

Spring 4_2 Chinook Forecasts

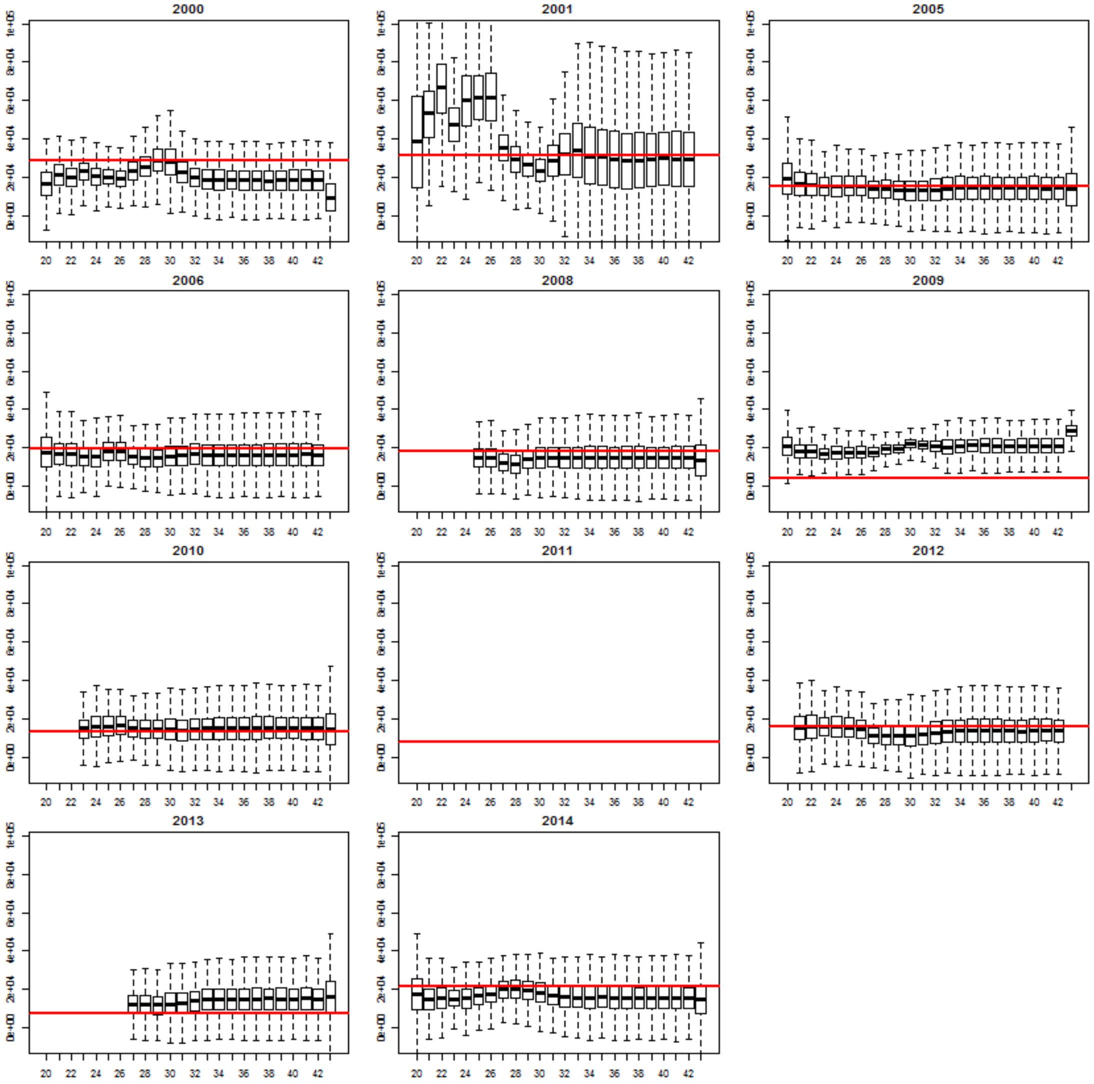


Figure D1. Annual forecasts of Spring 4_2 returns produced in the cross-validation analysis for the linear model. X-axes indicate statistical weeks, while the red line represent the true return in each year.

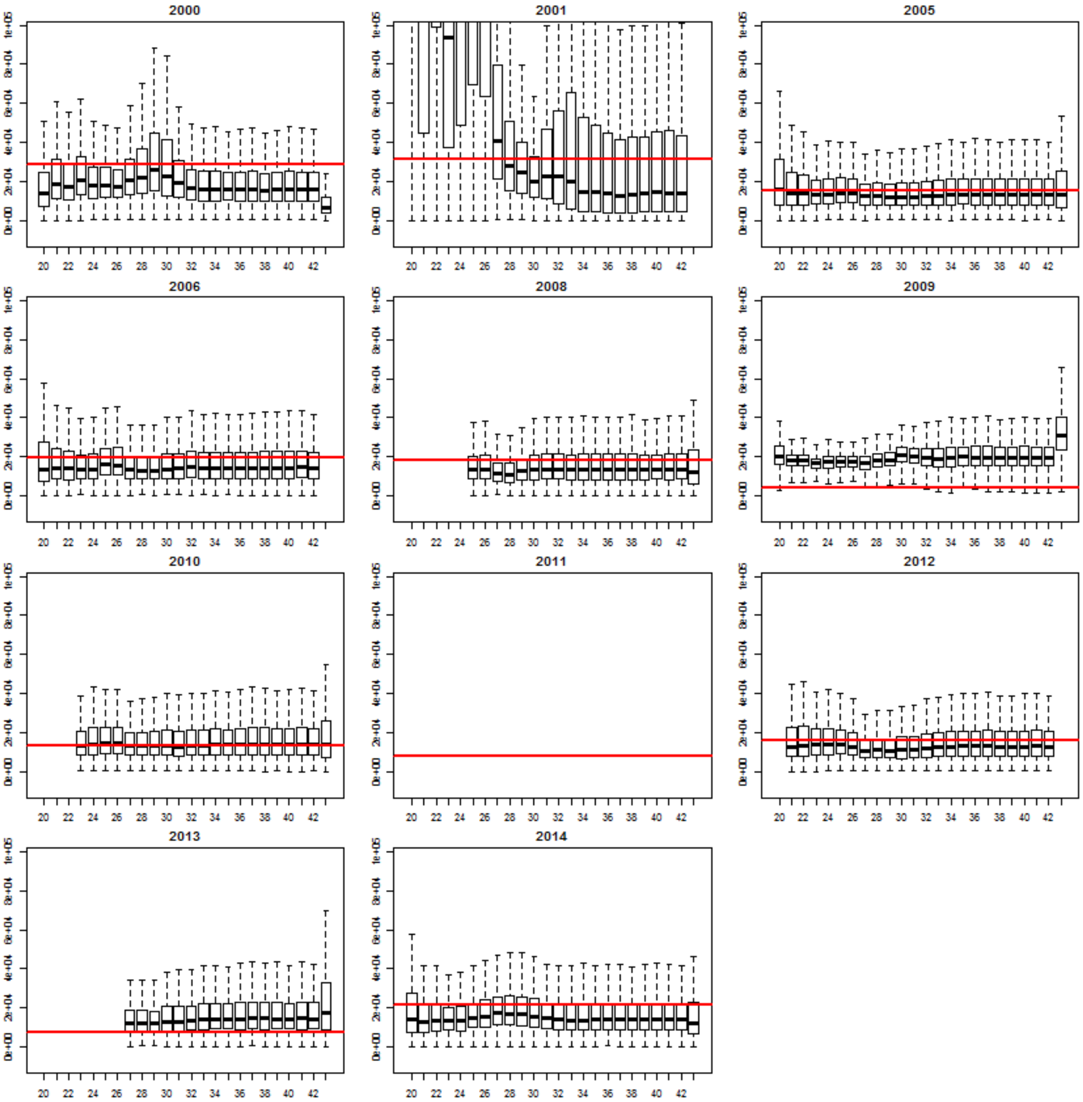


Figure D2. **Annual forecasts of Spring 4_2 returns produced in the cross-validation analysis for the exponential model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

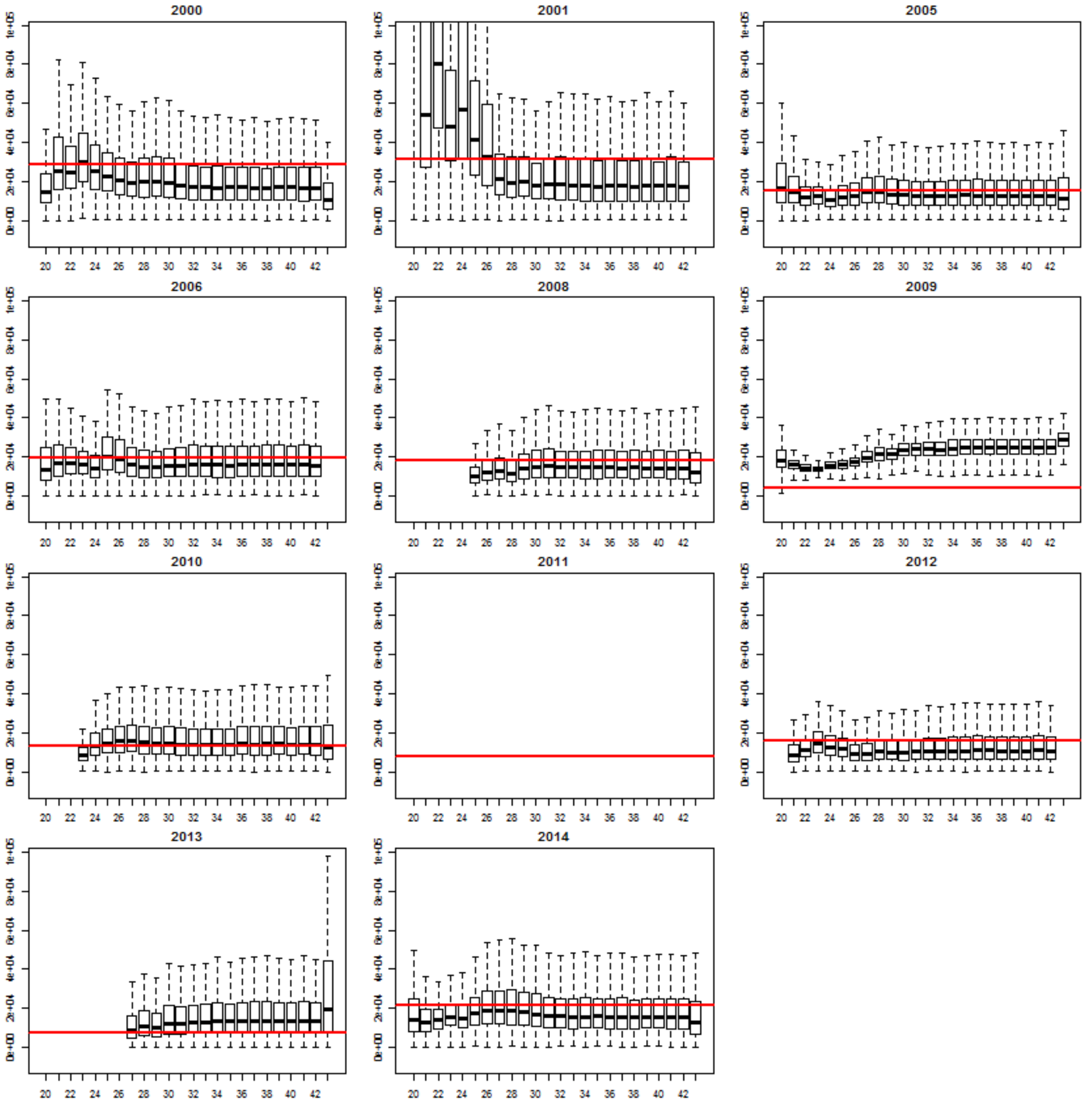


Figure D3. **Annual forecasts of Spring 4_2 returns produced in the cross-validation analysis for the allometric model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

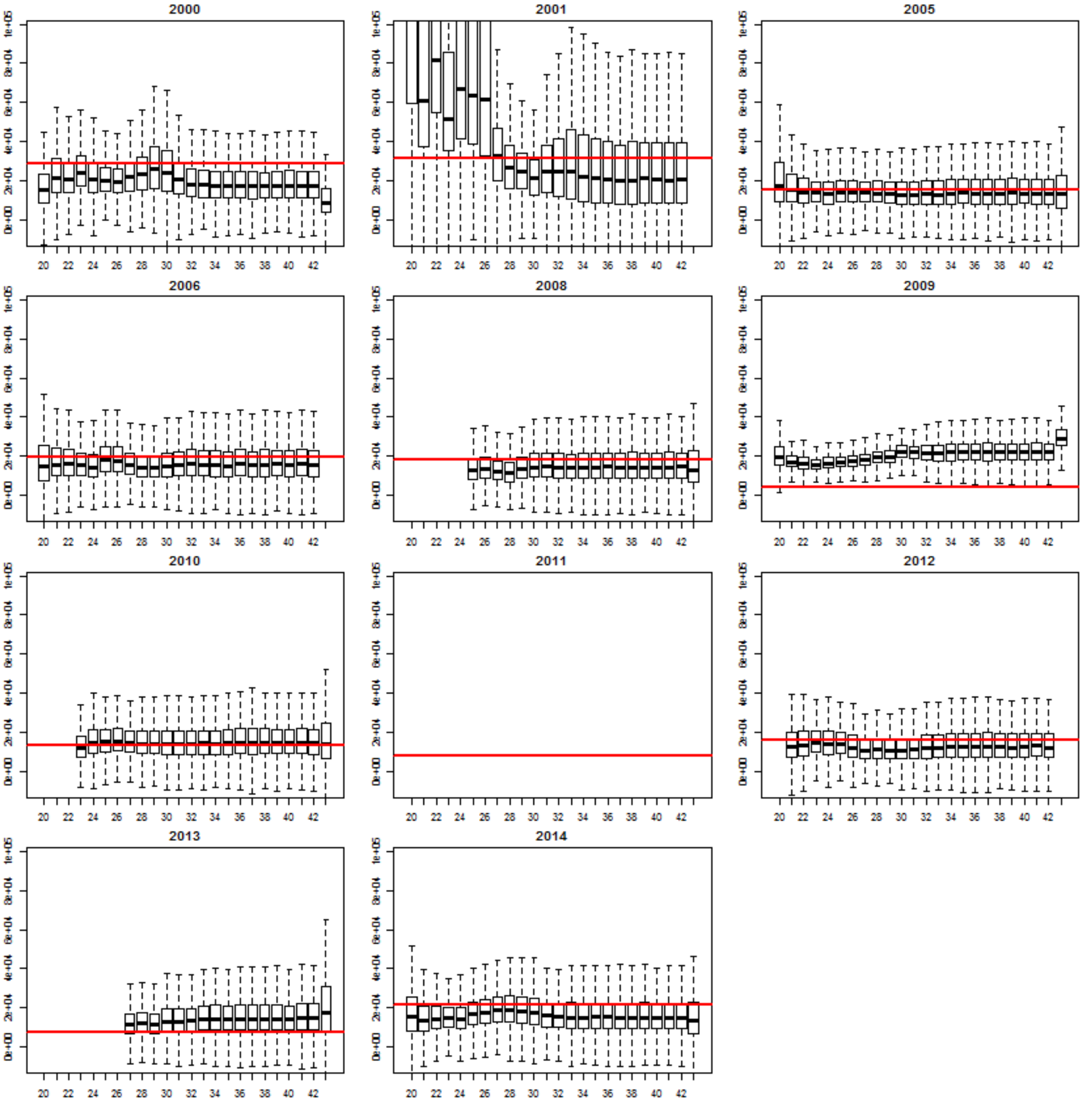


Figure D4. **Annual forecasts of Spring 4_2 returns produced in the cross-validation analysis for the composite model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

Spring 5_2 Chinook Forecasts

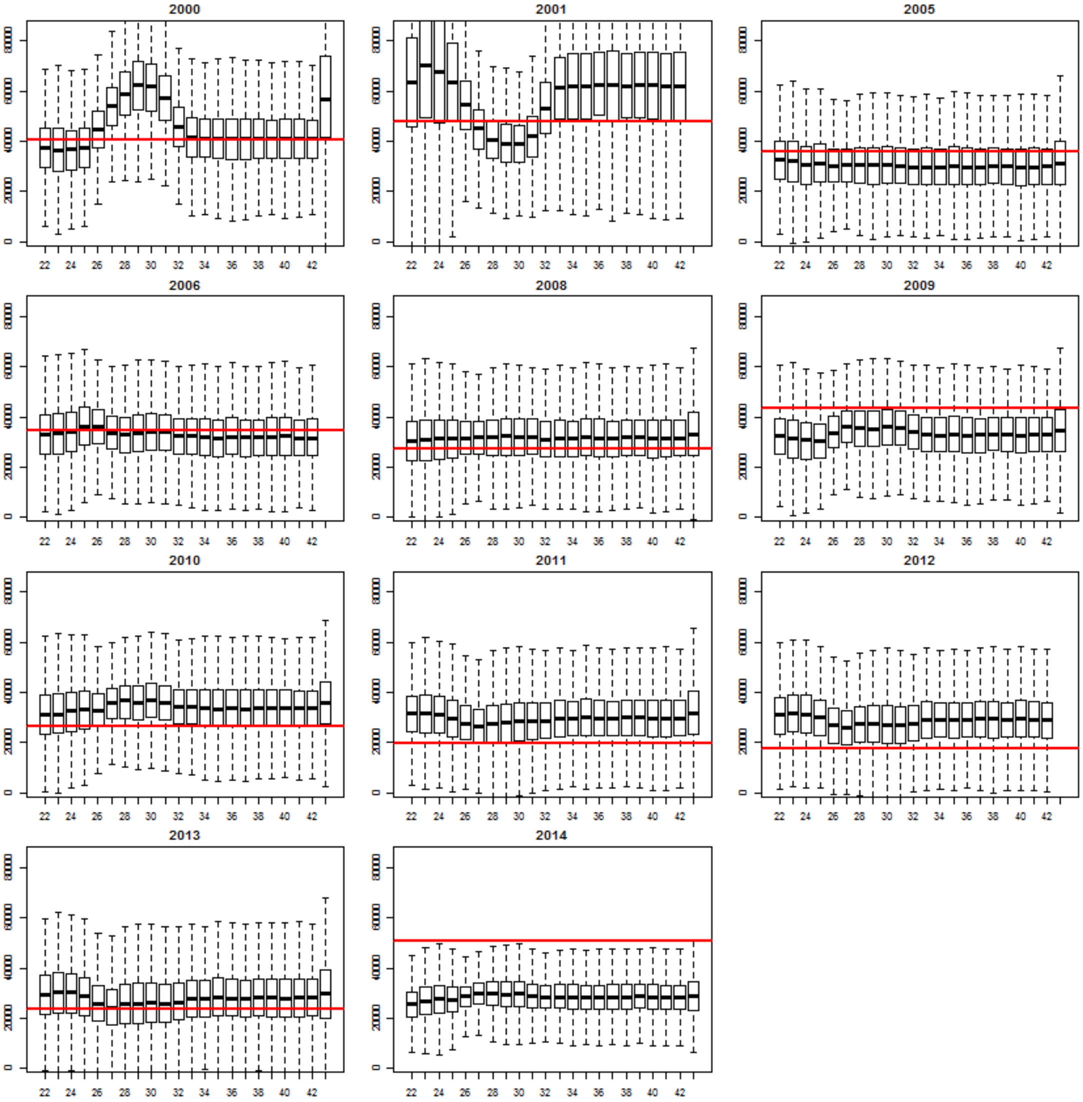


Figure D5. **Annual forecasts of Spring 5_2 returns produced in the cross-validation analysis for the linear model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

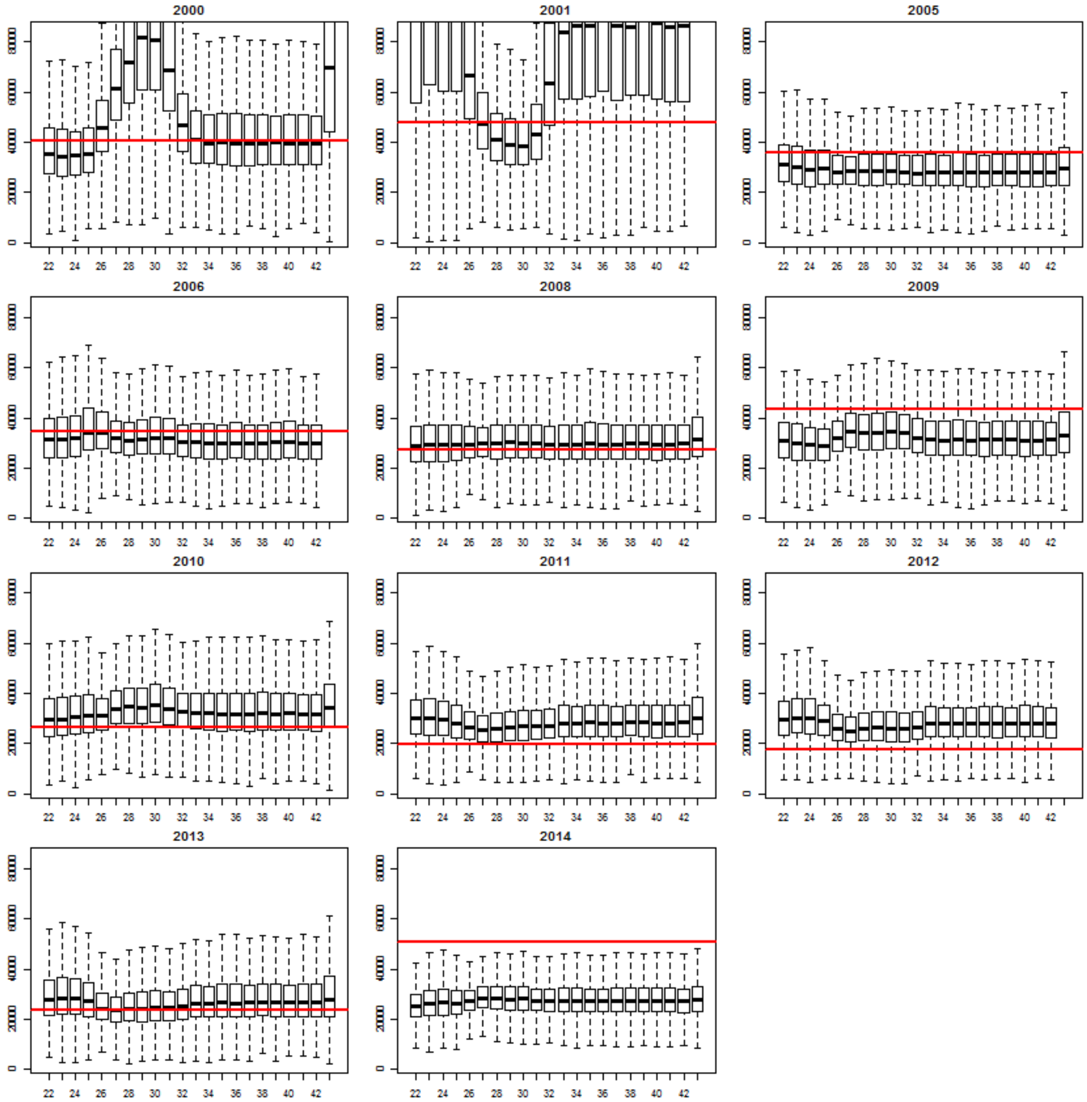


Figure D6. Annual forecasts of Spring 5_2 returns produced in the cross-validation analysis for the exponential model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.

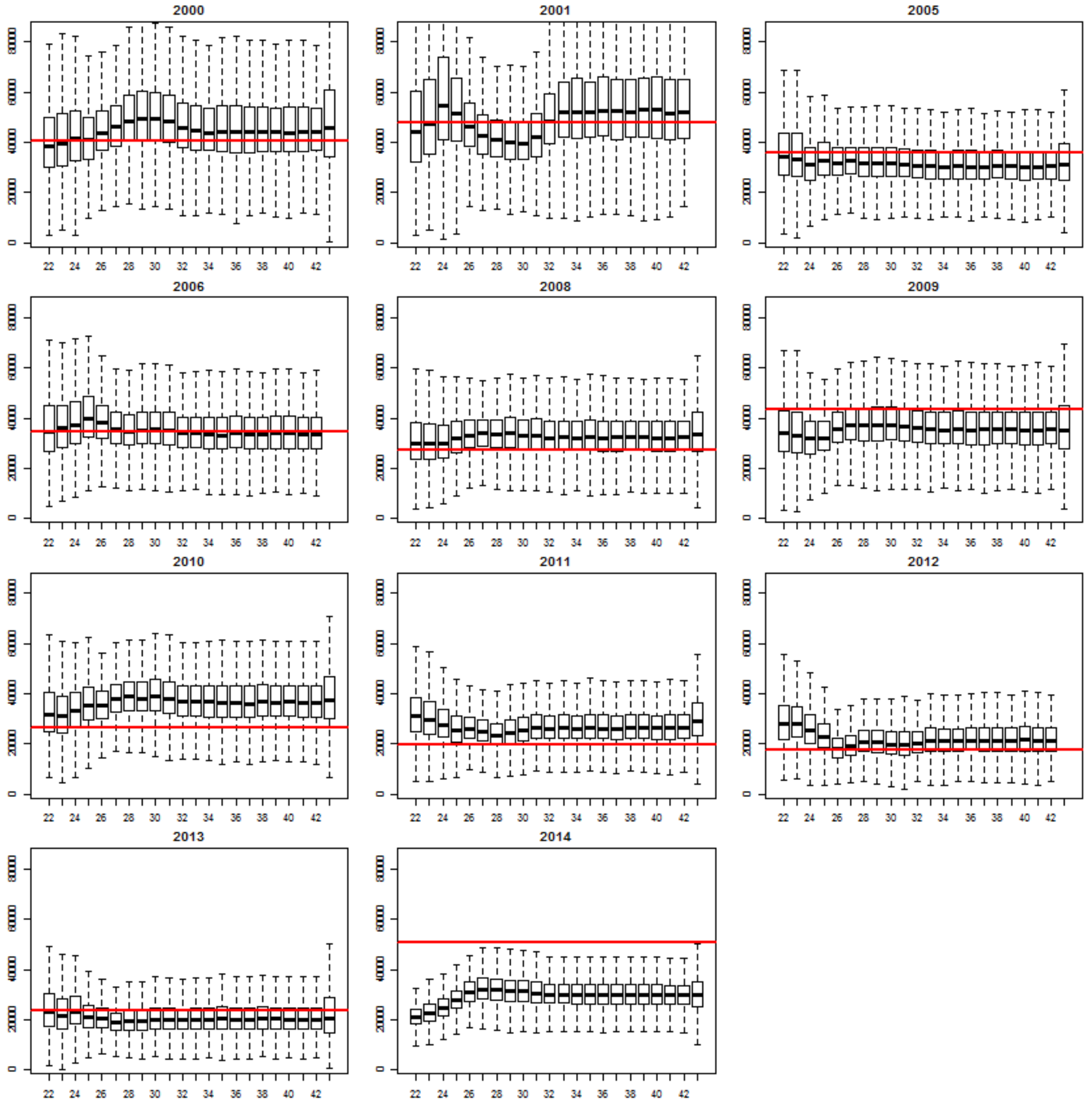


Figure D7. **Annual forecasts of Spring 5_2 returns produced in the cross-validation analysis for the allometric model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

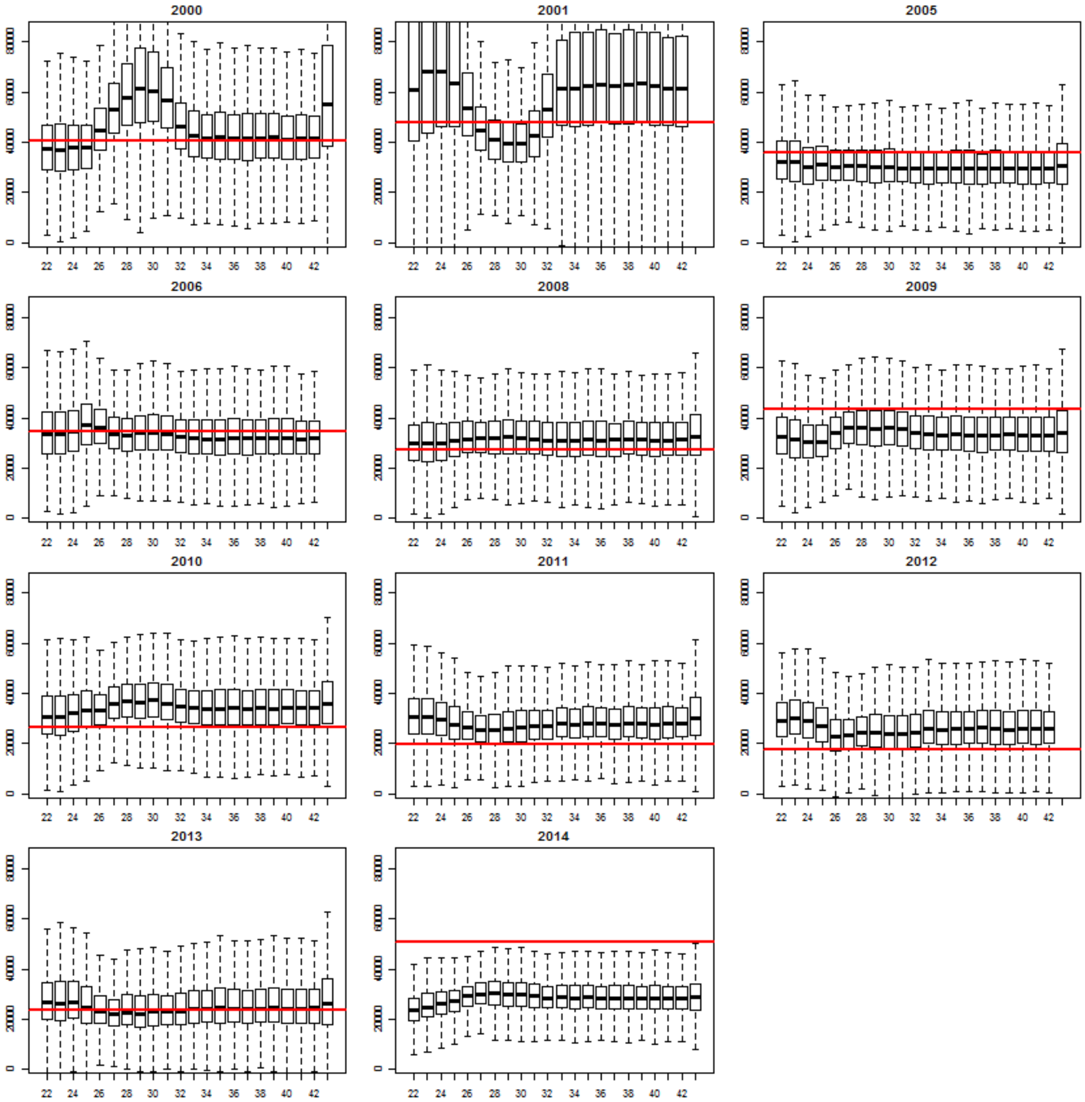


Figure D8. **Annual forecasts of Spring 5_2 returns produced in the cross-validation analysis for the composite model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

Summer 5_2 Chinook Forecasts

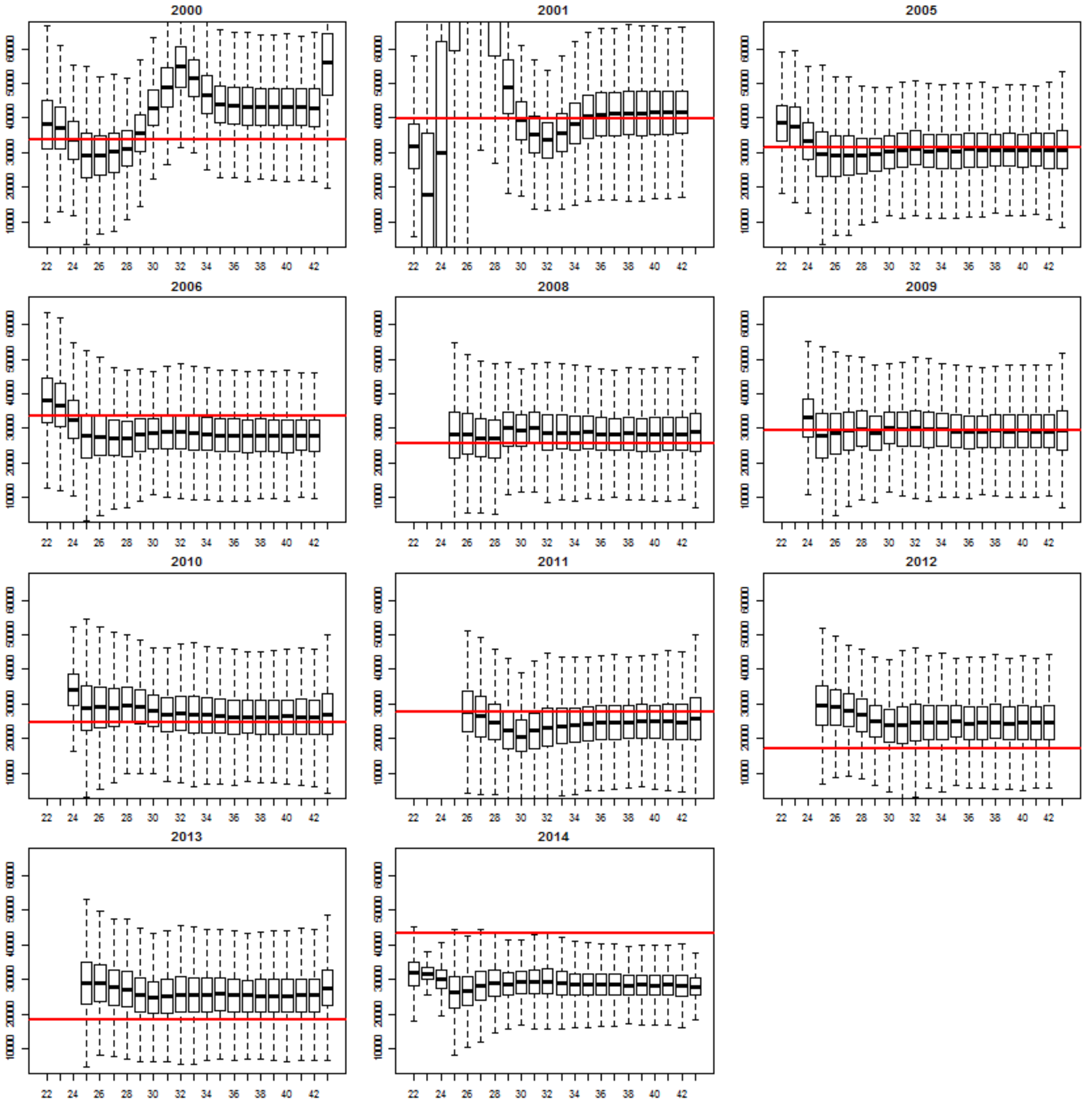


Figure D9. **Annual forecasts of Summer 5_2 returns produced in the cross-validation analysis for the linear model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

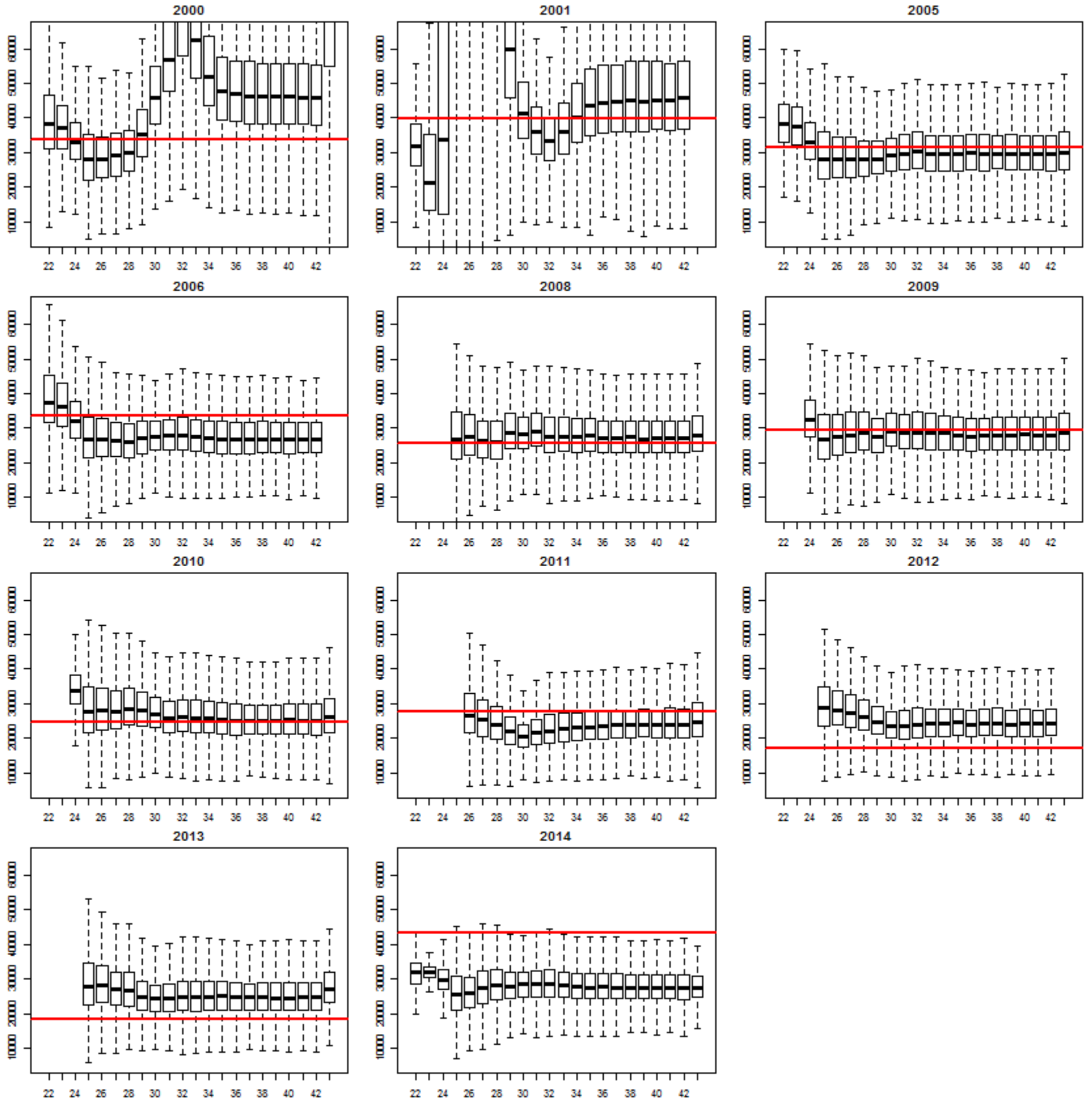


Figure D10. **Annual forecasts of Summer 5_2 returns produced in the cross-validation analysis for the exponential model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

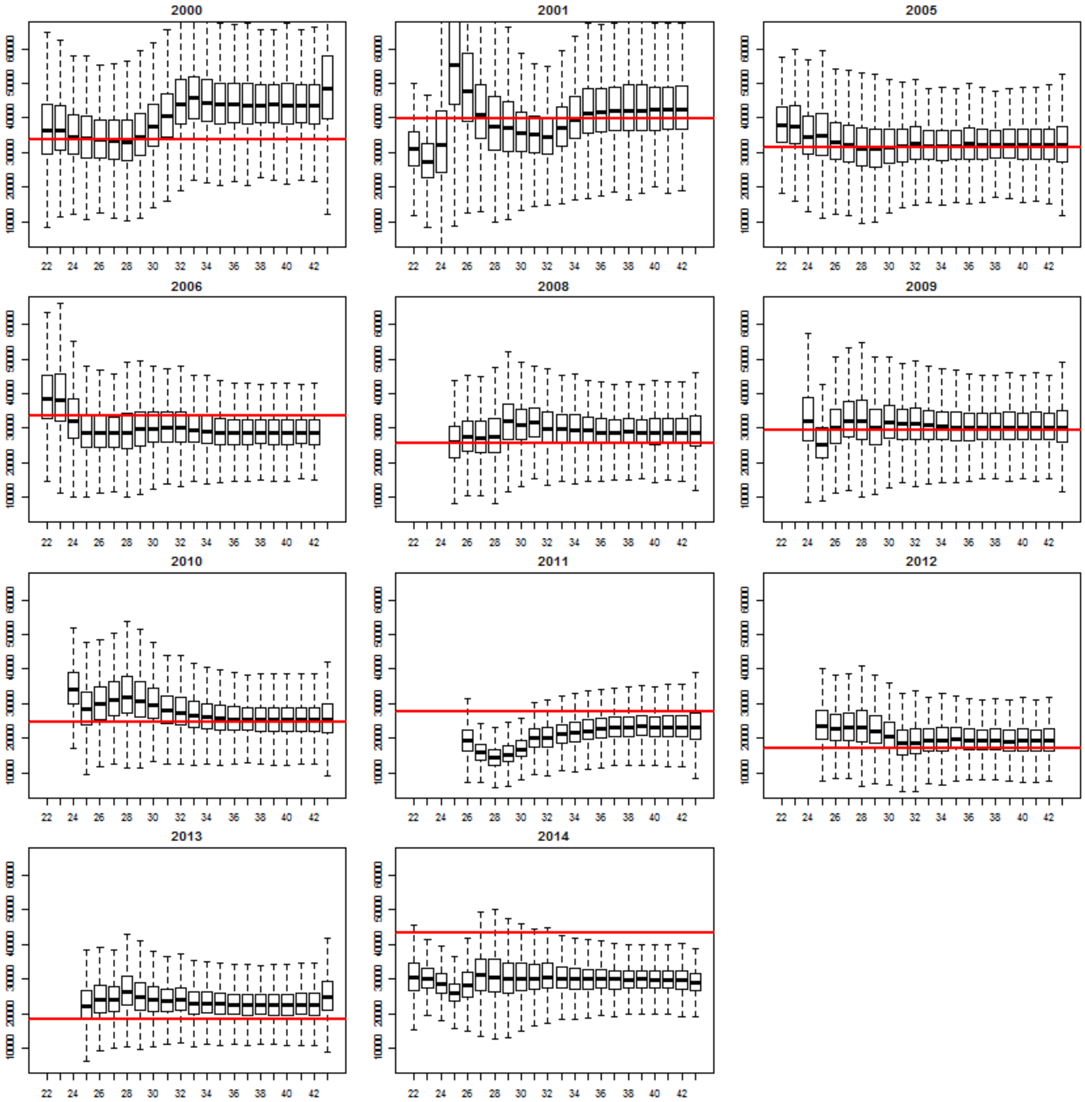


Figure D11. **Annual forecasts of Summer 5_2 returns produced in the cross-validation analysis for the allometric model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

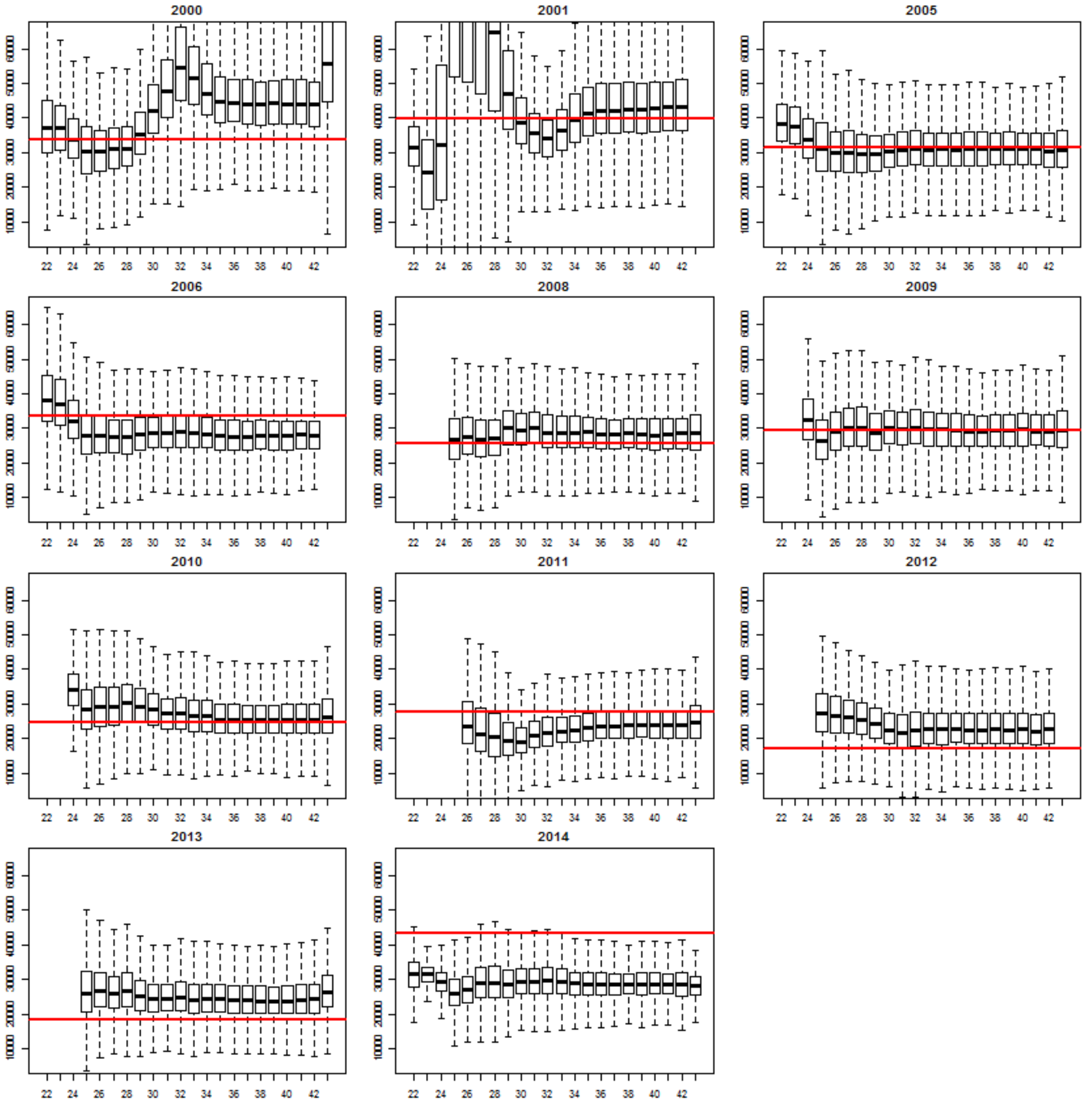


Figure D12. **Annual forecasts of Summer 5_2 returns produced in the cross-validation analysis for the composite model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

Summer 4_1 Chinook Forecasts

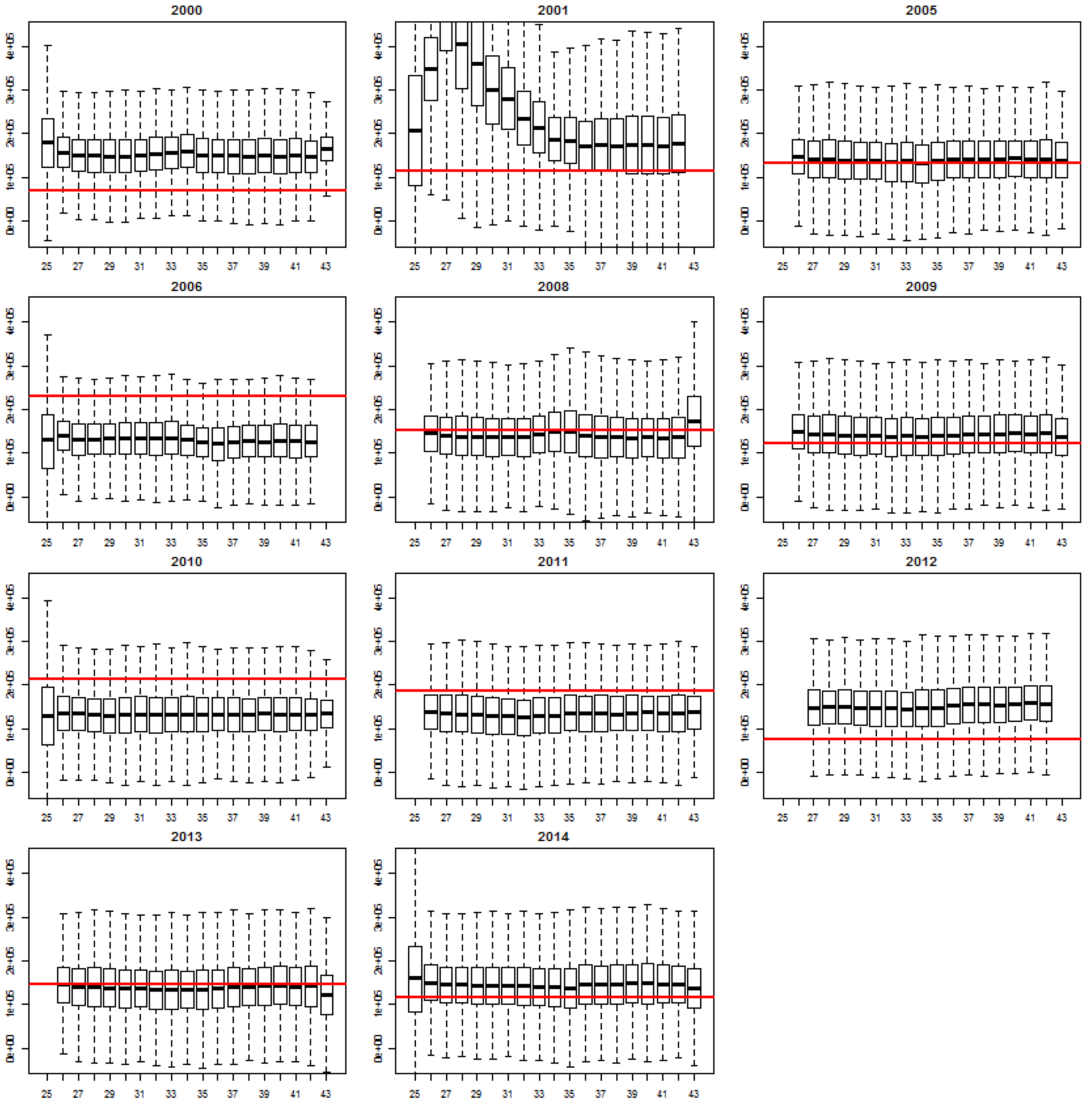


Figure D13. **Annual forecasts of Summer 4_1 returns produced in the cross-validation analysis for the linear model. X-axes indicate statistical weeks, while the red line represents the true return in each year.**

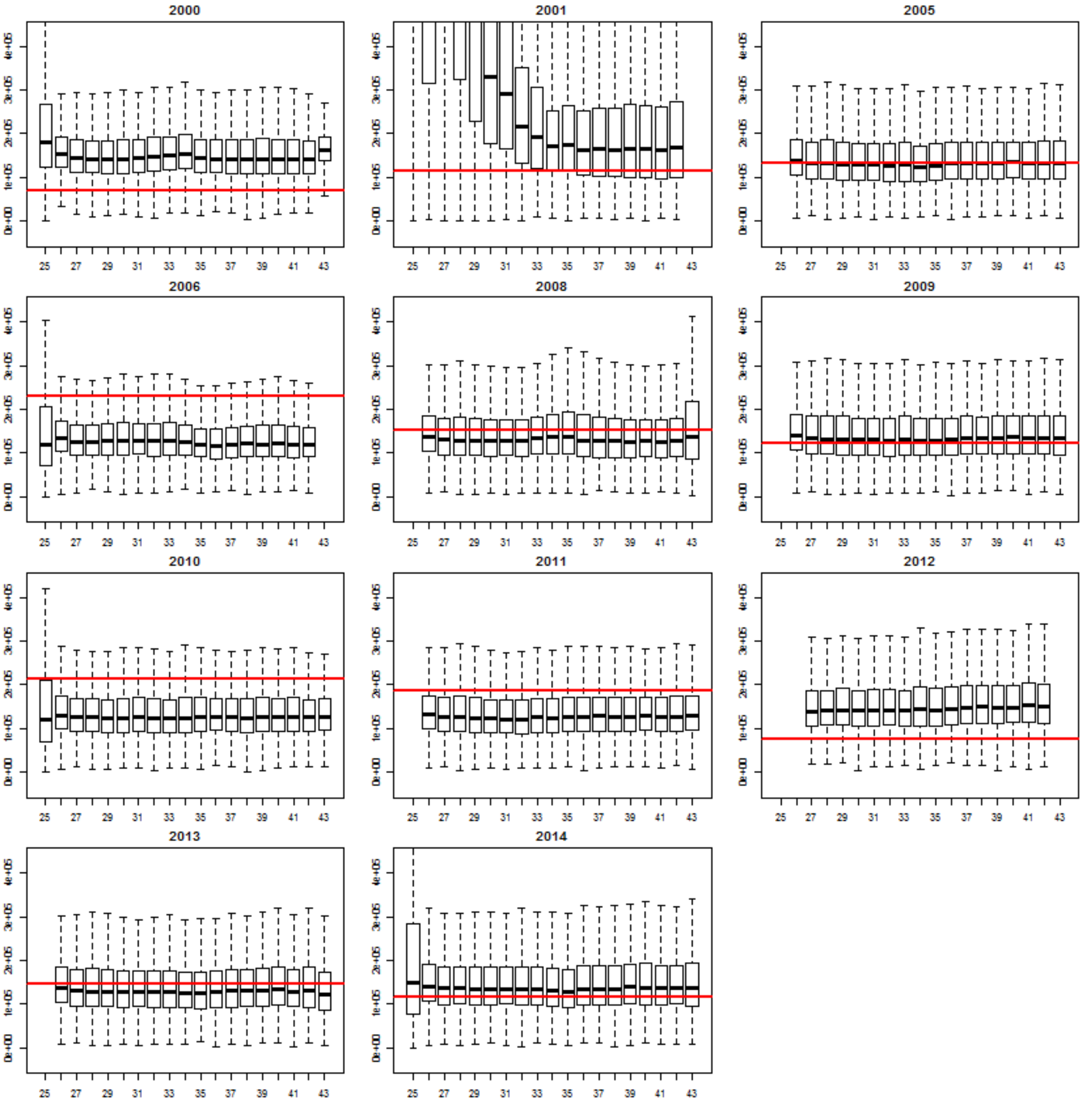


Figure D14. Annual forecasts of Summer 4_1 returns produced in the cross-validation analysis for the exponential model. X-axes indicate statistical weeks, while the red line represents the true return in each year.

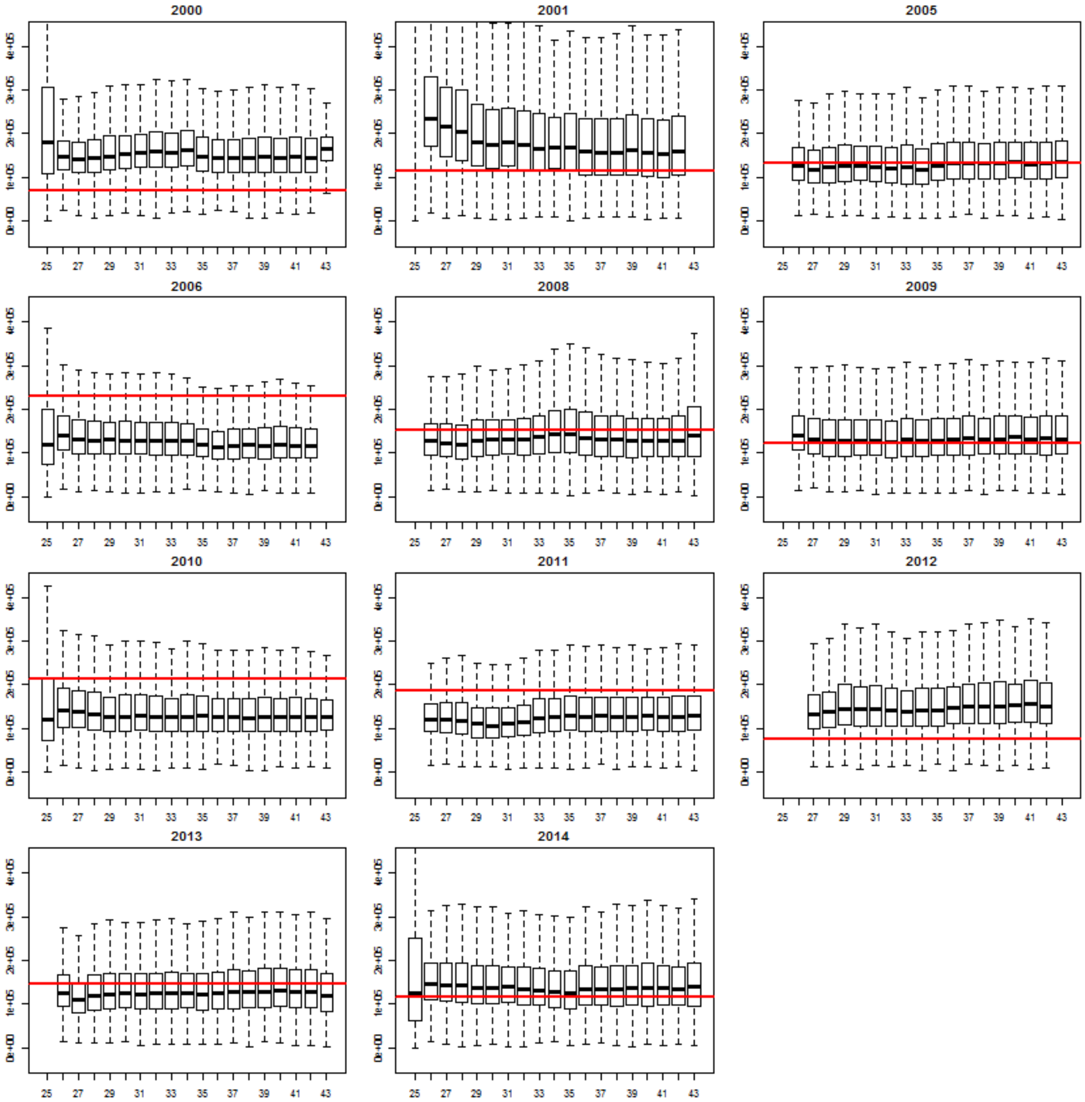


Figure D15. Annual forecasts of Summer 4_1 returns produced in the cross-validation analysis for the allometric model. X-axes indicate statistical weeks, while the red line represents the true return in each year.

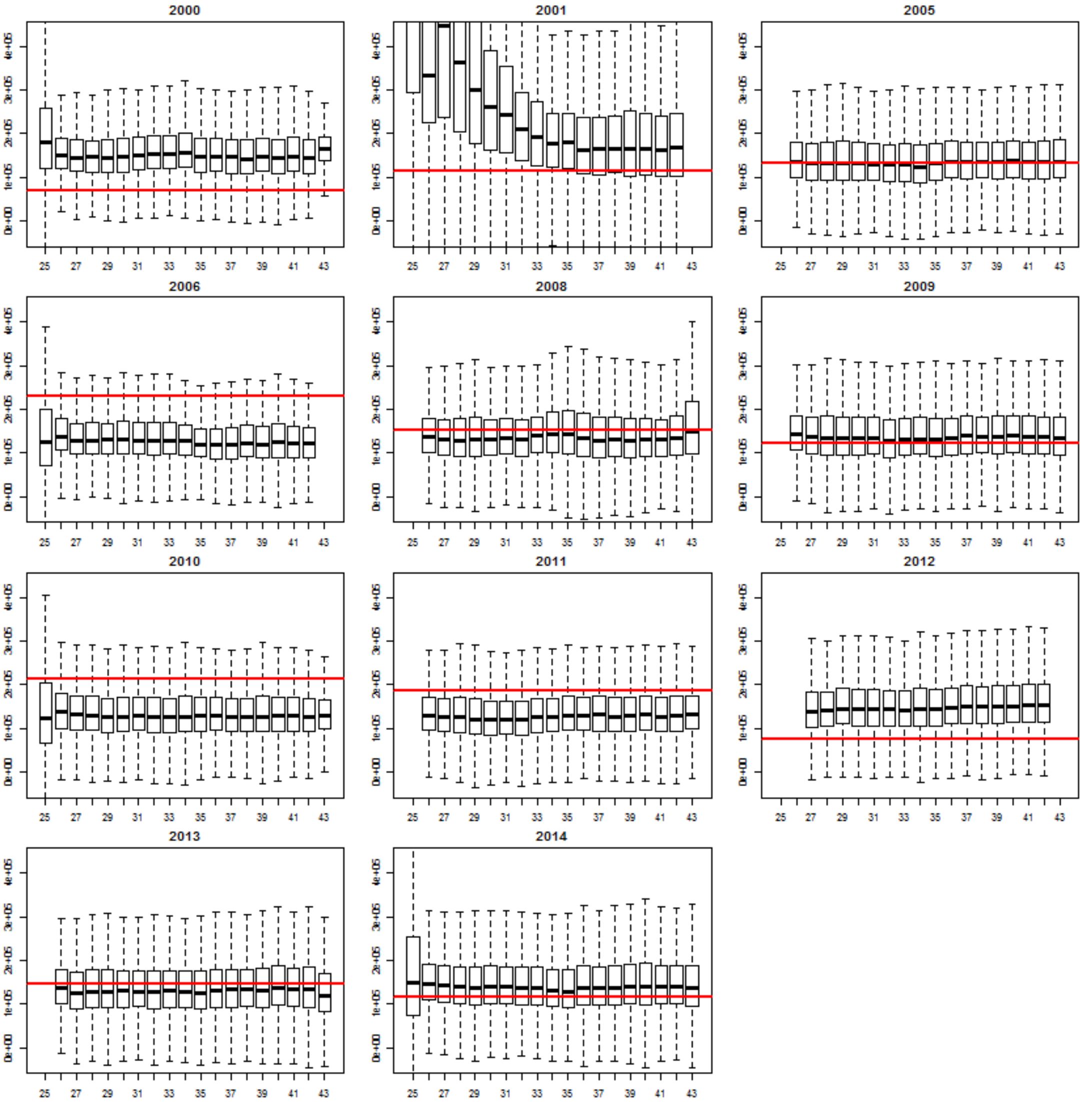


Figure D16. Annual forecasts of Summer 4_1 returns produced in the cross-validation analysis for the composite model. X-axes indicate statistical weeks, while the red line represents the true return in each year.

Fall Chinook Forecasts

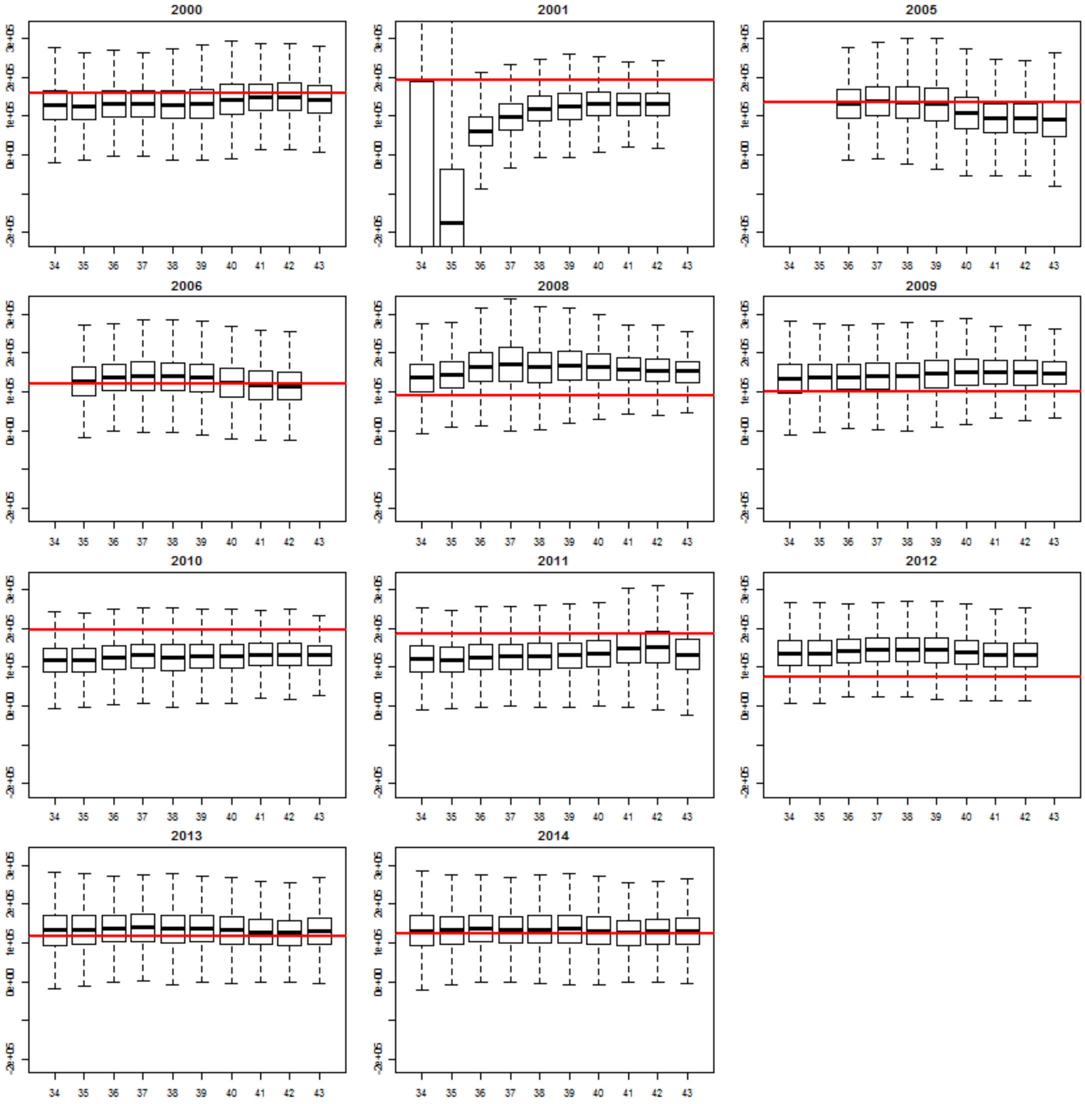


Figure D17. **Annual forecasts of Fall returns produced in the cross-validation analysis for the linear model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

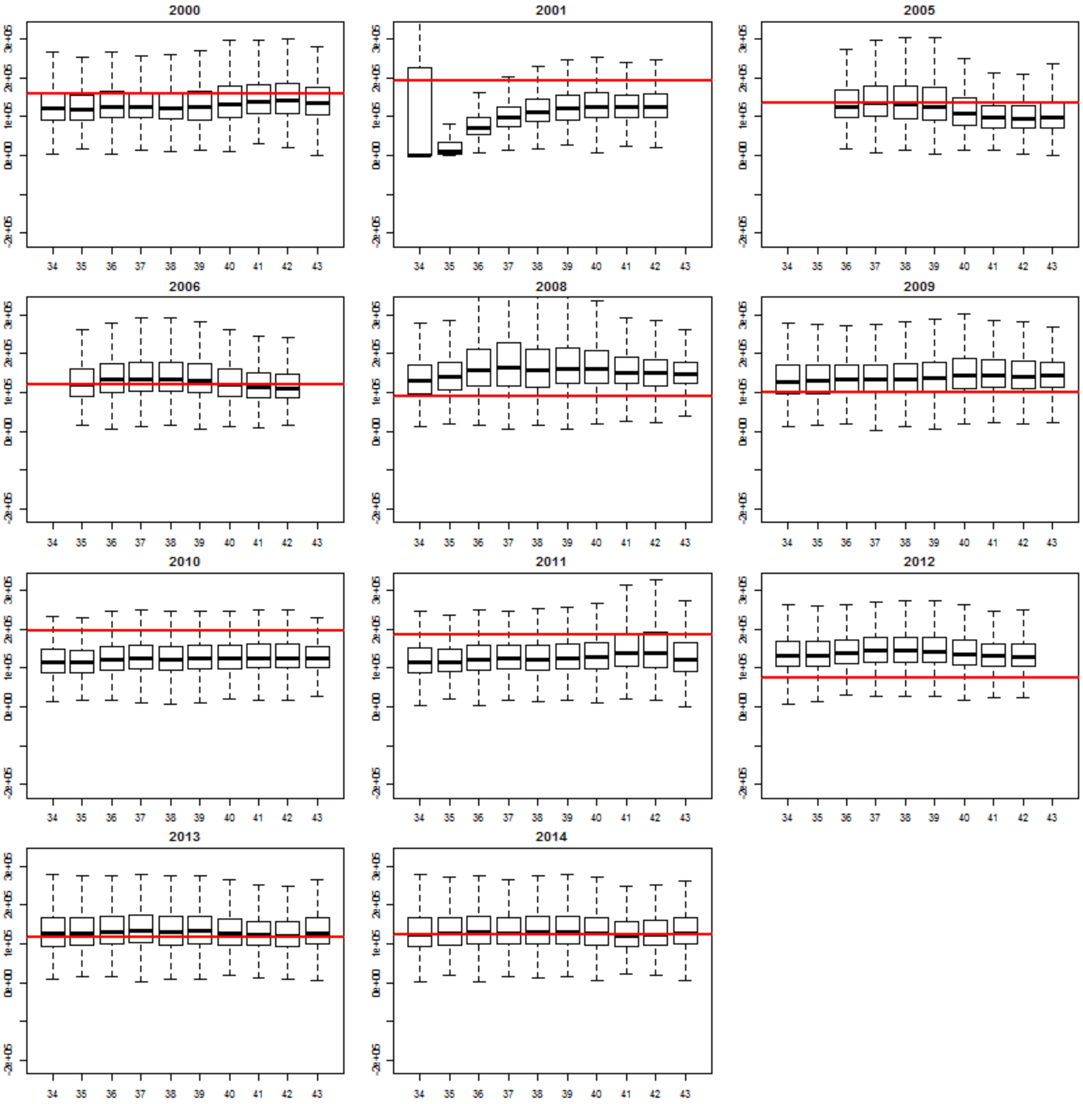


Figure D18. **Annual forecasts of Fall returns produced in the cross-validation analysis for the exponential model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

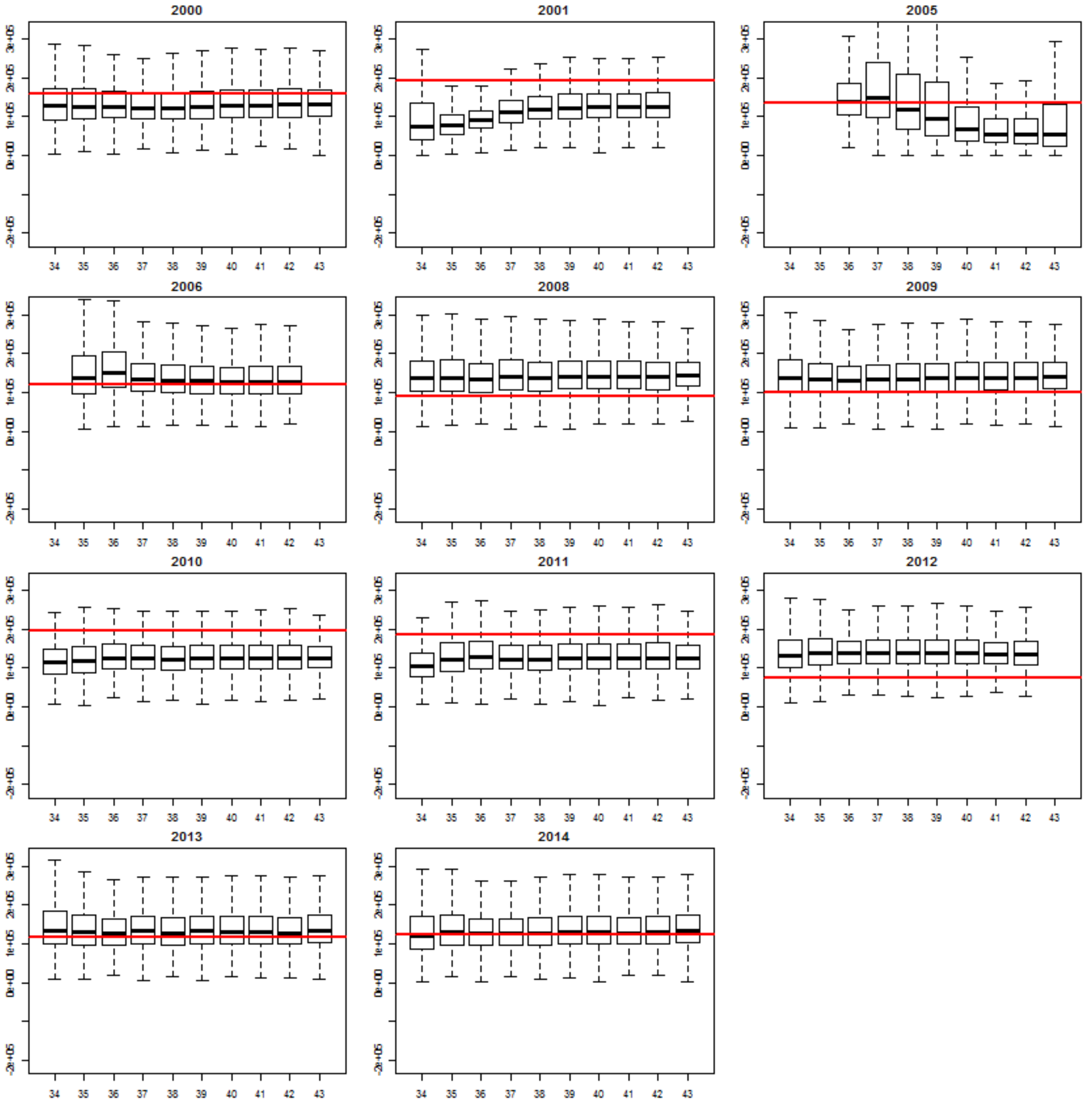


Figure D19. **Annual forecasts of Fall returns produced in the cross-validation analysis for the allometric model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**

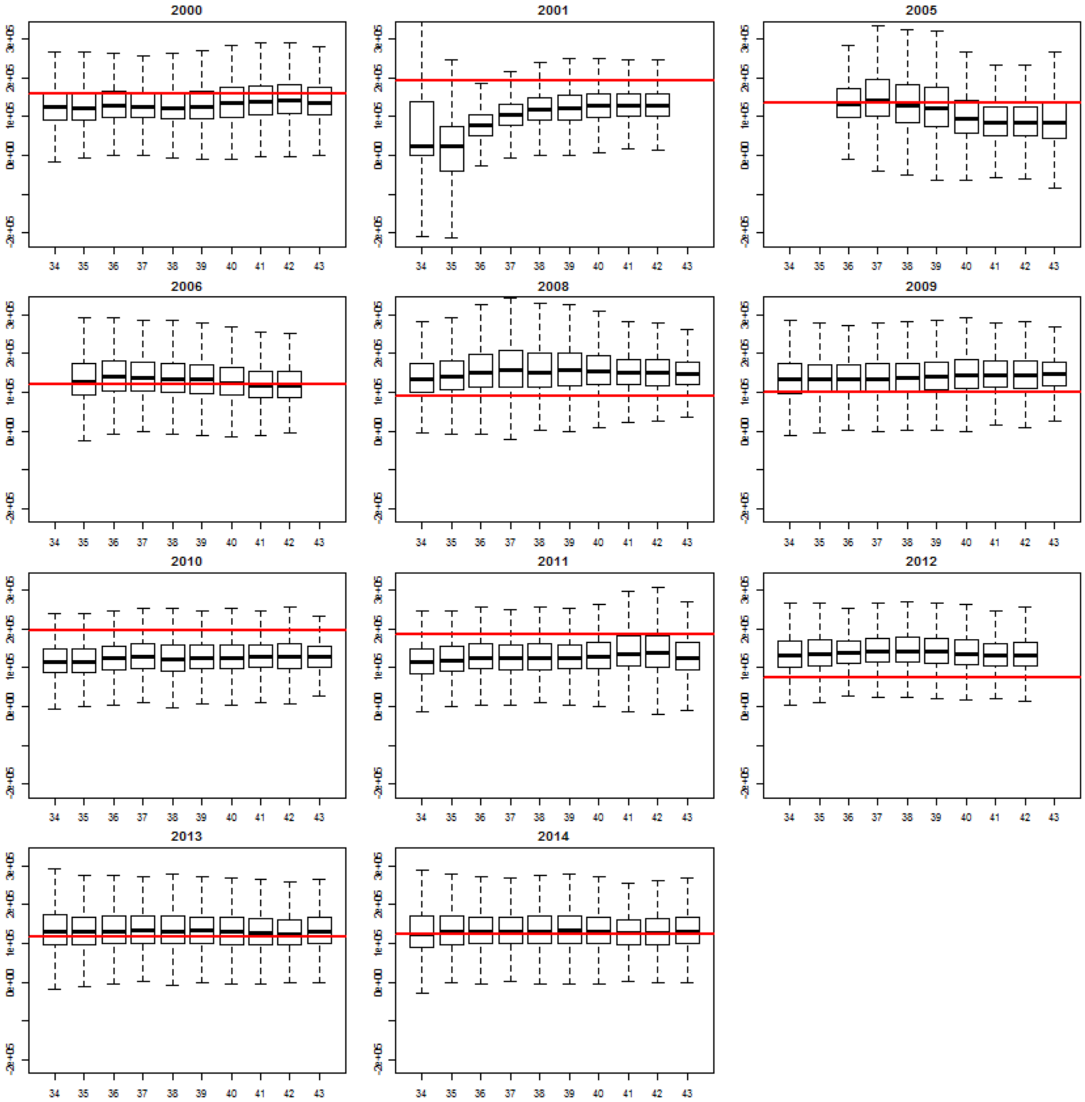


Figure D20. **Annual forecasts of Fall returns produced in the cross-validation analysis for the composite model (single panel data). X-axes indicate statistical weeks, while the red line represents the true return in each year.**