Chinook FRAM Base Period Documentation: Growth Functions

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BACKGROUND

To model fisheries with minimum size limit regulations, the Chinook Fishery Regulation Assessment Model (FRAM) is parameterized with growth functions for computing mean length (fork length, FL, in mm) by age and model time step, as well as supplementary inputs (coefficients of variation, CVs) for characterizing variability around these predictions. This report summarizes the data and analysis details associated with the growth parameters that were estimated in support of the 2015 Chinook FRAM Base Period Project. The objectives of this effort were to: (1) Estimate parameters for stock-specific von Bertalanffy growth functions (VBGFs), inclusive of an assessment of model fit diagnostics, etc.; and (2) Estimate stock-specific CVs associated with VBGF mean length-at-age predictions.

The approach taken differs from what has been done for prior base period (BP) calibrations in two important ways. Firstly, whereas past BPs included separate 'mature' (~terminal) and 'mixed-maturity' (~pre-terminal) VBGFs, a single pre-terminal model was deemed appropriate for contemporary modeling due to the lack of minimum size limits in terminal fisheries. Secondly, the estimation approach employed here addressed the fact that the data used to fit VBGFs (i.e., fishery recoveries) may be positively biased due to the release of sublegal/undersized (i.e., smaller than the minimum size limit) fish in fisheries with minimum size limit regulations.

DATA DESCRIPTION

This analysis is based on length observations associated with the coded-wire tag (CWT) recovery dataset selected for general base period calibration (i.e., exploitation rate estimation/cohort reconstruction) purposes, which is documented in other base period documents (i.e., stock profiles). Dataset details include:

- CWT recoveries for brood years 2005-2008 were included for all stocks. Additional CWT data were added to expand the sample size used to estimate VBGFs for the Washington Coast regional aggregate, as well as for the Sacramento/Central Valley stock; broods 2001-2004 were included for these two groups, as well as additional facilities for Washington Coast (Grays Harbor, Quinault, and Tsoo-Yess).
- Length data for CWTs processed via the CAS loading and FRAMBuilder mapping process were included in the analysis; 'anomalous' length data, such as from high-seas fisheries and/or research trawls, were excluded.
- Data collected in freshwater or extreme terminal fisheries, within which maturation-related changes in morphometry were expected to be well under way, were excluded from all analyses. Thus, although >90% of the dataset used here consists of pre-terminal recoveries, some terminal marine net recoveries were used in the final analysis.
- For cases in which CWT lengths were not reported in fork length (FL), conversions were made using the conversion equations of Conrad and Gutman (1996; total length) and Pahlke (1989; other length types).
- Data were combined across brood years and grouped into coarser regional aggregates (Table 1) in order to facilitate VBGF estimation (described below); aggregates were selected based on those used during the

estimation of growth parameters during the last Chinook FRAM calibration groupings and based on knowledge of stock relationships.

- The final analysis used data from 658 CWT codes and N = 27,535 marine recoveries (25,606 pre-terminal; 1,929 marine terminal net).

ESTIMATING GROWTH CURVE PARAMETERS

We used a two-stage approach to estimate growth functions for the Chinook FRAM Base Period project. In the first step, we estimated mean (μ_{sm}) and SD (σ_{sm}) length-at-age individual stock aggregate–month (*sm*) combinations using the method of Satterthwaite et al. (2012). In brief, this approach treats individual length observations as samples from a truncated normal distribution, wherein the truncation point is governed by the minimum size limit of a fishery; accordingly, it returns mean/SD maximum likelihood estimates (MLEs) consistent with both the observed and unobserved portions of the underlying probability distribution. Thus, the probability of observing an individual length l_i in a fishery with minimum length limit msl_i is

Equation 1. $$p(l_i|\mu_{sm},\sigma_{sm},msl_i) = \frac{\phi(l_i|\mu_{sm},\sigma_{sm}^2)}{1\text{-}\Phi(msl_i|\mu_{sm},\sigma_{sm}^2)}$$

and the probability for observing the length dataset as a whole ($\tilde{l}$) given the collective of size regulations ($\widetilde{msl}$) is simply the product of individual likelihoods, i.e.,

Equation 2. $$p(\tilde{l}|\mu_{sm},\sigma_{sm},\widetilde{msl}) = \prod_{i=1}^{N} p(l_i|\mu_{sm},\sigma_{sm},msl_i)$$

MLEs (μ_{sm},σ_{sm}) were generated using this joint likelihood function and the 'bbmle' package in R. For estimation purposes, we pooled data across brood years and did not attempt to estimate μ_{sm} and σ_{sm} unless there were at least 20 observations per month–stock aggregate estimation stratum. The μ_{sm} and σ_{sm} estimates generated through analysis stage 1 are provided in Appendix A. With the exception of two suspected outliers, the MLEs were consistent with the expected growth pattern for Chinook salmon and differed in the manner expected relative to values estimated in the absence of size limit considerations.

In our second estimation stage, we estimated the parameters of stock-specific von Bertalanffy growth functions (VBGFs) that best described variation in mean length-at-age estimates generated during stage one (i.e., μ_{sm}). To do this, we employed an approach wherein VGBF parameters were modeled to be stock-varying realizations from a common distribution of VBGF parameters (i.e., L_∞, k, t_0):

Equation 3. $$\mu_{sm} = L_{\infty_s}[1 - e^{(-k_s[t - t_{0s}])}] + \varepsilon_{sm}$$

Parameters were estimated using Bayesian methods in WinBUGS with uformative priors (see Appendix B for code, priors, and initial values). The final values proposed for inclusion in the Chinook FRAM BP are medians from a 1-in-50 sample of N = 31,000 MCMC iterations on each of three chains, less an N = 5,000 iteration burn-in period (i.e., N = 26K total per chain; Table 2). The fitted curves appear to describe well the variability in MLEs (stage 1 results), as well as raw length observations, on both a stock-by-stock (Figure 1) and overall (Figure 2) basis. Finally, we explored the sensitivity of stock-specific VBGF parameters to the inclusion/exclusion of two outliers (i.e., mean FL at age 21 and 29 months was lower than anticipated for Sacramento/CV stock; Appendix A). The omission of these points caused a small increase in the length-at-age prediction (fitted curve) for young Sacramento/Central

Valley fish and negligibly affected other stocks (Figure 1); the final VBGF parameters recommended for use in base period development exclude these two points.

In addition to mean length-at-age predictions, FRAM's size limit algorithm requires an estimate of distributional spread around means. We considered two approaches towards fulfilling this BP information need: (1) a constant CV approach, or (2) an age-varying CV approach. An inspection of stage 1 results (i.e., μ_{sm}, σ_{sm}) revealed that the latter method best captured patterns in the data (Figure 3). Thus, we used ANCOVA to assess the relationship between CV(FL) and age (in months) and then used the resulting model to compute CV(FL) on January 1 for age-2 to age-5 Chinook for use in modeling. ANCOVA results indicated that CV decreased significantly with increasing age overall ($P < 0.001$) and offered strong support for stock-specific intercepts ($P < 0.001$) but not slopes ($P > 0.05$). Thus, CV(FL) was computed, by age, for each regional aggregate based on an 'equal slopes' ANCOVA model (Appendix A).

FUTURE WORK

While the inputs proposed here for use in Chinook FRAM BP calibration are robust descriptors of length-at-age patterns for Chinook FRAM's model stocks, future work may consider improving on the present analysis in at least three ways. First, the estimation framework employed here necessitated that we group related stocks into larger regional aggregates, as was the case for previous base period calibrations. Although groupings were made with some consideration of stock relationships, a more objective approach guided by evidence in the length-at-age dataset may be preferable. This may, however, require an approach that avoids the two-stage analysis that introduced data restrictions here. Secondly, it may be possible to improve model accuracy, precision, and/or realism through the use of an alternative growth curve parameterization (e.g., with seasonally varying growth; O'Farrell et al. 2012). Although this may necessitate minor changes to FRAM algorithms, it may be beneficial, particularly if future changes alter FRAM's temporal structure. Lastly, whereas the curves reported here describe well the length-at-age patterns Chinook ages relevant to FRAM (i.e., ages 2 to 5), their utility in describing growth patterns for younger fish remains uncertain. If future FRAM applications necessitate prediction for younger ages, other length observations (e.g., length at release, for age-1 research trawl recoveries, etc.) should either be included in the analysis or used to corroborate predictions. We suggest that improvements such as these be given consideration during the phase II of the Chinook FRAM base period calibration.

REFERENCES

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Pahlke, K. 1989. Length conversion equations for sockeye, chinook, chum, and coho salmon in southeast Alaska. Juneau, AK: Alaska Department of Fish and Game, Division of Commercial Fisheries. 15 pp.

Satterthwaite, W. H., M. S. Mohr, M. R. O'Farrell, B. K. Wells, and C. Walters. 2012. A Bayesian hierarchical model of size-at-age in ocean-harvested stocks—quantifying effects of climate and temporal variability. Canadian Journal of Fisheries and Aquatic Sciences 69(5):942-954.

Table 1. Summary of data used to fit growth functions for FRAM model stock aggregates. Counts are based on marine fishery recoveries for brood years 2005-2008 for all stocks except for Washington Coast and Sacramento/Central Valley, which include additional recoveries, and non-model stock CWT codes, for brood years 2001-2004.

Regional Aggregate	Region Abbreviation	N observations by age				Stocks included
		Age 2	Age 3	Age 4	Age 5+	
Columbia River tule stocks	ColRTule	102	1,037	265	26	Lower River hatchery and natural tules, Bonneville Pool tules
Columbia River bright stocks	ColRUpriver	36	1,307	2,883	590	All Columbia River bright stocks (URB, upper Col. R summers, Lower R. wild)
Fraser Early	FraserEarly	1	225	385	7	Fraser Early all
Fraser Late	FraserLate	33	729	321	5	Fraser Late all
Lower Columbia R. spring	LColRSpr	5	192	580	156	Lower Columbia (Cowlitz, Kalama, Lewis) and Willamette spring stocks
Lower Georgia Strait	LGS	51	315	220	9	Lower Georgia Strait hatchery/natural fall stocks
North Puget Sound spring	NPSSprng	14	265	229	21	Skagit, Nooksack spring stocks
Oregon Coast	ORCoast	3	215	992	407	Oregon Coast fall stocks (NOC/MOC)
Puget Sound/Hood Canal summer/fall fingerling	PSHCfng	156	3,024	2,196	74	All Puget Sound/Hood Canal summer/fall fingerling stocks
Puget Sound/Hood Canal summer/fall yearling	PSHCyrl	4	226	349	24	All Puget Sound/Hood Canal summer/fall yearling stocks
Sacramento/Central Valley	Sacramento	234	3,313	296	2	Sacramento/Central Valley stocks
Washington Coast	WACoast	13	229	2,901	2,253	Willapa Bay, Grays Harbor, WA North Coast, etc.
West Coast Vancouver Island	WCVI	7	79	414	115	West Coast Vancouver Island hatchery/natural (Robertson stock)

Table 2. Estimates of VBGF parameters by regional stock aggregate. Estimates are median values (95% credible intervals in parentheses) from a 1-in-50 sample of N = 26K MCMC iterations (i.e., 31K less 5K burn-in period) on each of three chains. Final parameter estimates are based on an analysis that excludes Sacramento outliers (See App A).

Regional Aggregate	L_∞	***k***	t_0
ColRTule	942 (845-1101)	0.049 (0.031-0.077)	6.5 (1.3-10.8)
ColRUpriver	966 (881-1121)	0.036 (0.024-0.051)	6.9 (1.3-12.8)
FraserEarly	934 (832-1109)	0.048 (0.029-0.072)	5.3 (-2-10.7)
FraserLate	1072 (949-1300)	0.038 (0.024-0.058)	6.5 (1.1-12)
LColRSpr	945 (853-1106)	0.053 (0.032-0.082)	3.9 (-2.4-8.7)
LGS	920 (839-1056)	0.048 (0.031-0.068)	4.9 (-0.9-9.2)
NPSSprng	978 (853-1219)	0.038 (0.024-0.058)	6.9 (1.7-12.6)
ORCoast	940 (878-1042)	0.043 (0.03-0.059)	6.1 (-0.3-11.6)
PSHCfng	952 (859-1079)	0.04 (0.029-0.057)	5.3 (1.6-8.7)
PSHCyrl	1013 (857-1485)	0.035 (0.018-0.055)	7.4 (2-14.6)
Sacramento	1010 (923-1170)	0.047 (0.03-0.068)	5.3 (0.3-9.1)
WACoast	988 (923-1100)	0.041 (0.028-0.057)	6.6 (0.4-12.7)
WCVI	934 (849-1071)	0.045 (0.03-0.066)	5.6 (-1.5-11.1)

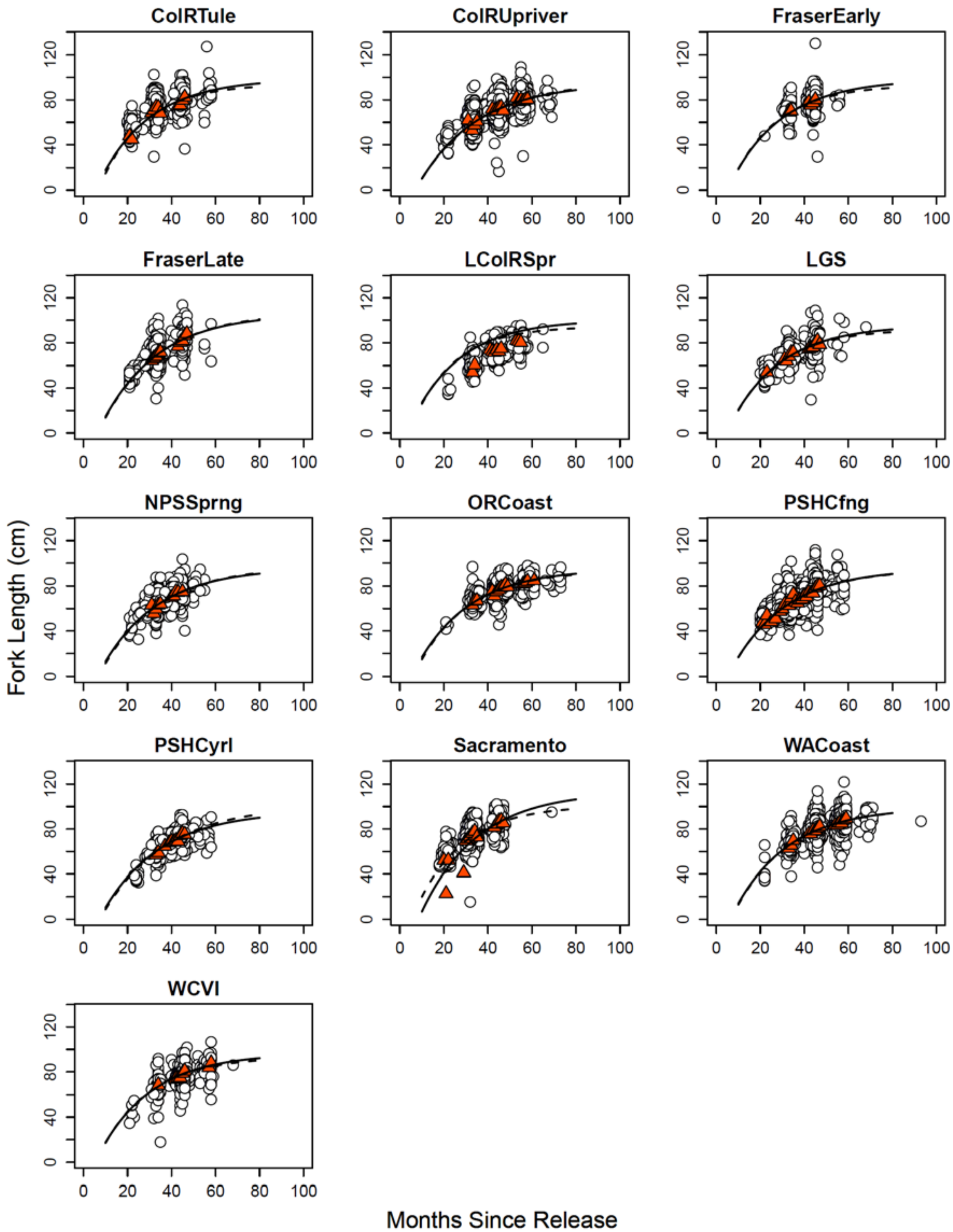

Figure 1. Growth functions for regional aggregates of FRAM model stocks. In each figure, white circles represent individual observations whereas red triangles are monthly means for (min. month N = 20). Note, monthly means were estimated via maximum likelihood assuming that tags recovered in fisheries with minimum size restrictions are a truncated sample (see 'Stage 1 analysis' in text for details). The dashed line in each figure reflects the VBGF parameterization resulting from withholding two Sacramento outliers.

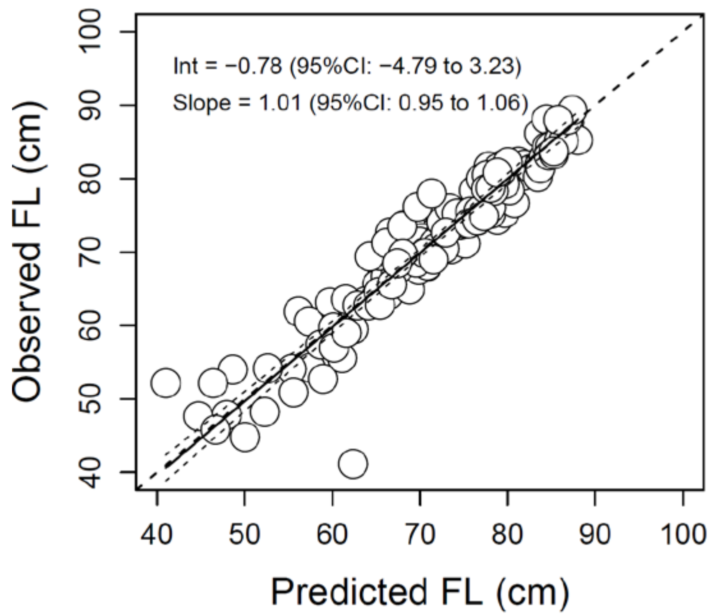

Figure 2. VBGF-predicted vs. observed fork length by stock-month observation. A posterior predictive check indicated good correspondence between the model and data (Bayesian P-value = 0.52).

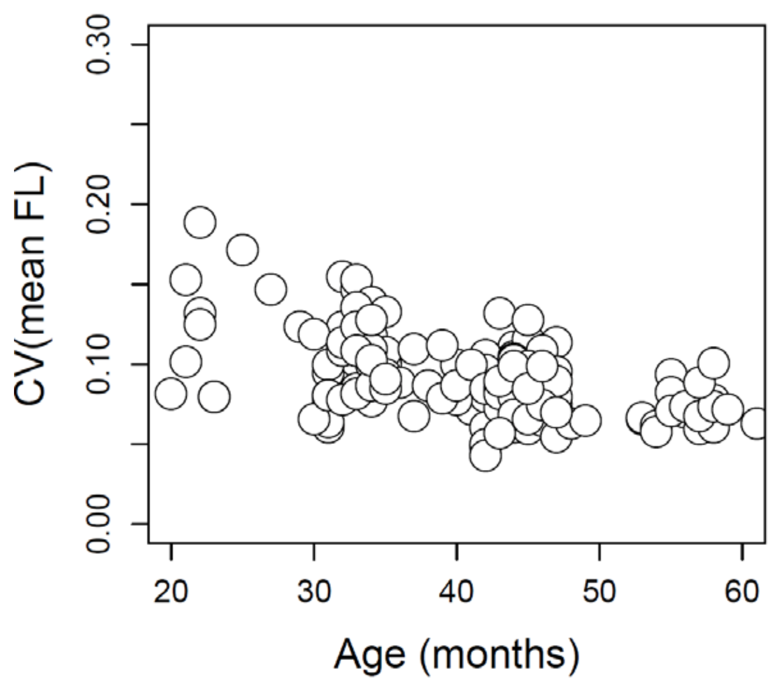

Figure 3. Coefficient of variation associated with monthly length-at-age estimates.

APPENDIX A. LENGTH-AT-AGE DISTRIBUTION PARAMETERS

Table A1. Stage 1 analysis results. Maximum likelihood estimates of the mean, SD, and CV of fork length (FL, mm) by age (in months) for stock-time estimation strata for which sufficient records occurred to estimate distributional parameters (N = 20). Note, the two suspected outliers that were included in VBGF estimation but not in the CV function analysis are denoted by '**'; columns 'Age' and 'Mean FL (cm)' are the values used for fitting VBGFs.

Region	Age (months)	N	Mean FL (cm)	SD	CV(FL)
ColRTule	21	23	47.9	7.3	15.3%
ColRTule	22	48	44.9	8.5	18.9%
ColRTule	31	170	68.3	6.5	9.5%
ColRTule	32	423	70.8	7.8	11.1%
ColRTule	33	206	73.7	7.5	10.2%
ColRTule	34	154	73.3	7.5	10.3%
ColRTule	35	23	68.0	6.9	10.2%
ColRTule	43	44	74.5	6.1	8.2%
ColRTule	44	70	75.4	8.4	11.1%
ColRTule	45	81	79.7	8.7	10.9%
ColRTule	46	38	82.4	7.3	8.8%
ColRUpriver	31	41	61.9	4.8	7.7%
ColRUpriver	32	194	54.3	8.4	15.5%
ColRUpriver	33	338	52.8	7.7	14.7%
ColRUpriver	34	461	57.5	8.0	13.9%
ColRUpriver	35	65	60.8	6.1	10.0%
ColRUpriver	42	95	71.9	6.7	9.3%
ColRUpriver	43	555	69.9	5.6	8.0%
ColRUpriver	44	806	70.3	6.3	9.0%
ColRUpriver	45	595	73.0	6.1	8.4%
ColRUpriver	46	599	73.6	6.2	8.5%
ColRUpriver	47	74	70.4	8.0	11.4%
ColRUpriver	53	31	81.7	5.4	6.6%
ColRUpriver	54	58	78.3	4.9	6.3%
ColRUpriver	55	133	79.9	7.5	9.4%
ColRUpriver	56	154	78.9	6.2	7.9%
ColRUpriver	57	97	79.9	6.0	7.5%
ColRUpriver	58	49	80.4	6.3	7.8%
FraserEarly	33	141	69.2	5.9	8.5%
FraserEarly	34	41	70.3	7.7	10.9%
FraserEarly	42	40	77.9	5.5	7.1%
FraserEarly	43	47	75.3	7.6	10.1%
FraserEarly	44	127	77.3	7.8	10.0%
FraserEarly	45	142	80.3	7.7	9.6%
FraserLate	31	72	64.7	6.5	10.0%
FraserLate	32	194	66.5	7.2	10.9%
FraserLate	33	184	68.0	8.4	12.4%
FraserLate	34	147	70.9	8.3	11.8%
FraserLate	35	90	71.7	7.7	10.8%
FraserLate	43	56	76.7	6.5	8.4%
FraserLate	44	67	80.5	7.4	9.2%
FraserLate	45	88	81.9	8.8	10.7%
FraserLate	46	63	86.2	8.3	9.6%
FraserLate	47	21	88.1	6.6	7.5%
LColRSpr	21	56	54.1	6.9	12.8%

Region	Age (months)	N	Mean FL (cm)	SD	CV(FL)
LColRSpr	22	73	60.7	5.2	8.5%
LColRSpr	29	26	73.8	5.3	7.2%
LColRSpr	30	53	72.0	3.5	4.9%
LColRSpr	31	113	71.5	5.9	8.3%
LColRSpr	32	130	73.8	6.0	8.2%
LColRSpr	33	99	72.3	5.7	7.9%
LColRSpr	34	106	74.9	4.9	6.5%
LColRSpr	41	22	82.0	5.5	6.7%
LColRSpr	42	30	81.4	5.1	6.2%
LColRSpr	43	35	80.3	6.6	8.3%
LGS	23	29	54.2	4.3	8.0%
LGS	31	40	65.6	4.0	6.1%
LGS	32	72	64.2	7.6	11.8%
LGS	33	67	67.8	8.4	12.5%
LGS	34	52	71.2	6.1	8.6%
LGS	35	42	71.5	6.2	8.7%
LGS	42	20	74.4	7.9	10.6%
LGS	43	26	75.0	9.9	13.2%
LGS	44	43	76.1	8.0	10.5%
LGS	45	32	79.8	9.3	11.6%
LGS	46	36	81.9	8.9	10.9%
LGS	47	22	78.5	7.5	9.6%
NPSSprng	31	33	63.2	4.0	6.4%
NPSSprng	32	48	55.6	6.9	12.4%
NPSSprng	33	51	59.6	9.1	15.3%
NPSSprng	34	47	63.3	8.8	13.9%
NPSSprng	35	24	64.1	8.5	13.3%
NPSSprng	40	46	70.1	7.0	10.0%
NPSSprng	41	25	71.3	6.7	9.4%
NPSSprng	42	24	75.0	6.0	8.0%
NPSSprng	43	20	74.4	6.2	8.4%
NPSSprng	45	23	75.0	9.6	12.8%
ORCoast	33	57	63.3	7.3	11.6%
ORCoast	34	101	66.7	5.2	7.7%
ORCoast	35	33	67.2	6.3	9.4%
ORCoast	42	22	75.4	4.6	6.1%
ORCoast	43	51	71.2	5.9	8.3%
ORCoast	44	137	75.0	4.6	6.1%
ORCoast	45	366	76.8	4.6	6.0%
ORCoast	46	331	78.9	5.1	6.5%
ORCoast	47	46	79.3	4.3	5.5%
ORCoast	48	57	81.5	5.1	6.3%
ORCoast	49	30	79.3	5.1	6.5%
ORCoast	56	48	81.8	5.8	7.0%
ORCoast	57	111	82.9	4.9	6.0%
ORCoast	58	75	84.4	5.1	6.1%
ORCoast	61	24	85.0	5.4	6.3%
PSHCfng	21	25	47.7	4.9	10.2%
PSHCfng	22	36	45.8	6.1	13.2%
PSHCfng	23	48	54.0	4.3	8.0%
PSHCfng	25	20	48.3	8.3	17.2%
PSHCfng	27	20	51.0	7.5	14.7%
PSHCfng	29	46	57.5	7.1	12.4%

Region	Age (months)	N	Mean FL (cm)	SD	CV(FL)	
PSHCfng	30	25	59.8	7.1	11.9%	
PSHCfng	31	165	63.7	5.2	8.1%	
PSHCfng	32	469	62.8	7.2	11.4%	
PSHCfng	33	627	62.8	8.5	13.6%	
PSHCfng	34	1,038	69.6	7.0	10.0%	
PSHCfng	35	427	72.7	6.5	9.0%	
PSHCfng	36	43	65.9	5.9	8.9%	
PSHCfng	37	53	65.0	7.1	11.0%	
PSHCfng	38	40	67.6	5.9	8.7%	
PSHCfng	39	54	68.2	7.6	11.2%	
PSHCfng	40	112	70.7	5.5	7.8%	
PSHCfng	41	87	70.6	6.5	9.1%	
PSHCfng	42	65	74.1	7.2	9.7%	
PSHCfng	43	225	73.7	5.4	7.3%	
PSHCfng	44	317	73.9	7.7	10.4%	
PSHCfng	45	346	78.5	7.8	9.9%	
PSHCfng	46	616	80.1	6.8	8.5%	
PSHCfng	47	215	80.5	6.4	8.0%	
PSHCyrl	33	65	57.0	7.0	12.4%	
PSHCyrl	34	100	59.0	6.5	11.0%	
PSHCyrl	37	22	64.6	4.4	6.8%	
PSHCyrl	39	20	67.8	5.3	7.9%	
PSHCyrl	40	36	69.0	6.0	8.7%	
PSHCyrl	41	21	68.7	6.9	10.0%	
PSHCyrl	42	20	69.8	6.0	8.5%	
PSHCyrl	43	22	69.1	5.9	8.5%	
PSHCyrl	44	39	74.1	7.6	10.3%	
PSHCyrl	45	84	76.1	7.6	9.9%	
PSHCyrl	46	57	75.3	6.9	9.2%	
Sacramento	20	29	52.2	4.3	8.2%	
Sacramento	21	76	22.8	14.2	62.1%	**
Sacramento	22	62	52.2	6.5	12.5%	
Sacramento	29	42	41.2	9.9	24.1%	**
Sacramento	30	276	69.5	4.6	6.6%	
Sacramento	31	760	71.3	5.8	8.1%	
Sacramento	32	772	73.6	5.7	7.8%	
Sacramento	33	786	76.2	6.3	8.2%	
Sacramento	34	454	78.0	6.8	8.7%	
Sacramento	35	140	72.7	6.2	8.5%	
Sacramento	43	90	81.5	6.7	8.2%	
Sacramento	44	53	84.4	6.7	8.0%	
Sacramento	45	67	87.2	5.9	6.7%	
Sacramento	46	29	87.7	7.7	8.8%	
Sacramento	47	29	85.3	7.7	9.0%	
WACoast	33	42	62.8	6.8	10.9%	
WACoast	34	134	65.7	6.7	10.3%	
WACoast	35	20	69.8	6.3	9.1%	
WACoast	42	57	75.6	3.8	5.0%	
WACoast	43	66	75.6	6.8	9.0%	
WACoast	44	397	78.6	5.4	6.9%	
WACoast	45	1,276	78.4	5.2	6.6%	
WACoast	46	965	80.9	6.1	7.5%	
WACoast	47	116	82.3	5.8	7.0%	

Region	Age (months)	N	Mean FL (cm)	SD	CV(FL)
WACoast	54	102	83.2	4.8	5.8%
WACoast	55	58	83.4	6.0	7.1%
WACoast	56	369	85.2	6.3	7.4%
WACoast	57	936	85.2	5.8	6.8%
WACoast	58	615	88.0	6.5	7.4%
WACoast	59	74	89.4	6.5	7.2%
WCVI	34	38	68.6	8.8	12.8%
WCVI	42	41	74.0	3.2	4.3%
WCVI	43	21	74.4	4.3	5.7%
WCVI	44	103	75.0	7.4	9.9%
WCVI	45	110	78.8	6.7	8.5%
WCVI	46	113	80.9	8.0	9.9%
WCVI	57	24	83.8	7.4	8.9%
WCVI	58	20	88.0	8.9	10.1%

APPENDIX B. WINBUGS CODE FOR FITTING GROWTH FUNCTIONS

```
##WinBUGS code for VB Growth fxn #####
### Specs for FRAM VBGF parameter estimation:
## N = 3 chains, thinned to 1 in 50
## N = 31k total interations (1k initial, 30k thereafter, summarize 5001+)
model
{
	# priors
	mu.a0~dnorm(0, 0.001) # Mean hyperparameter for a0
	mu.Linf~dnorm(0, 0.001) # Mean hyperparameter for Linf
	mu.k~dnorm(0, 0.001) # Mean hyperparameter for k
	sigma.a0~dunif(0, 10000) # SD hyperparameter for a0
	sigma.Linf~dunif(0, 10000) # SD hyperparameter for Linf
	sigma.k~dunif(0, 10000) # SD hyperparameter for k
	sigma~dunif(0, 10000) # Residual standard deviation
	tau.a0 <- 1/(sigma.a0*sigma.a0)
	tau.Linf <- 1/(sigma.Linf*sigma.Linf)
	tau.k <- 1/(sigma.k*sigma.k)
	tau <- 1/(sigma*sigma) # Residual precision

	# hierarchical parmeters
	for (i in 1:P) {
		Linf[i]~dnorm(mu.Linf, tau.Linf)
		k[i]~dnorm(mu.k, tau.k)#I(0,)
		a0[i]~dnorm(mu.a0, tau.a0)
	}

	# likelihood
	for (i in 1:N) {
		li[i] ~ dnorm(Lai[i],tau)
		Lai[i]<-Linf[pop[i]]*(1-exp(-k[pop[i]]*(ai[i]-a0[pop[i]])))
		# Observation-level GOF calcs
		pred[i] <- Lai[i]
		rep_li[i] ~ dnorm(pred[i], tau)   #simulate perfect dataset
		rep_resid[i] <- rep_li[i]-pred[i]   #calc resid for simulated data
		resid[i] <- li[i] - pred[i]   #calc resid for actual data
		sq[i] <- pow(resid[i],2)  #calc squared resids for actual data
		sq_new[i] <- pow(rep_resid[i],2)   #calc squared resids for simulated data
	}
	# Dataset-level GOF calcs
	fit<-sum(sq[]) #sum squared resids for actual data
	fit_new<-sum(sq_new[]) #sum squared resids for simulated data
	test<-step(fit_new-fit) #determine which is greater (0s and 1s)
	bpvalue<-mean(test) #mean of 0,1 gives Bayesian P-value
}

# inits
list(a0=c(-5,-5,-5,-5,-5,-5,-5,-5,-5,-5,-5,-5,-5), k=c(0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03,0.03),
Linf=c(950,950,950,950,950,950,950,950,950,950,950,950,950),mu.a0=-
5,mu.k=0.03,mu.Linf=950,sigma.a0=1,sigma.Linf=1,sigma.k=1,sigma=1)

#data -- also must load secondary data file (Appendix A) with stock-month means
list(N=164, P=13) #n is 165 observations (0 indexed) and 13 stock aggregates
```