Evidence of range-wide patterns in growth for northeast pacific sablefish using a new data-driven detection method

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# Introduction

Sablefish (*Anoplopoma fimbria*) are a highly mobile, long-lived, valuable groundfish that have high movement rates (10 – 88% annual movement probabilities across Alaska, Hanselman et al. 2015) and range from Southern California to the Bering Sea. Concurrent sablefish population declines across the entire range during the past few decades have increased concern about the populations’ status and causes of this downward trend. Traditionally, sablefish stock assessment and management has occurred independently at regional scales, namely Alaska, British Columbia, and the US West Coast, assuming that these are closed stocks. However, recent genetic work has shown that NE Pacific sablefish are not genetically distinct between these traditional management areas (Jasonowicz et al., 2017), though there is evidence for differences in growth rate and size-at-maturity throughout the range (McDevitt, 1990). This suggests that the current delineation of assessment and management regions is incongruent with the stock’s actual spatial structure and motivates research that would enable the construction of a population dynamics model which represents the spatial heterogeneity of sablefish throughout their range.

Growth rates of fish within a population, which are generally parameterized using the von Bertalanffy growth function (VBGF, von Bertalanffy, 1957) can influence stock assessment results (Punt, 2003). Parameter estimates for sablefish are usually based on survey data acquired from chartered commercial trawl or longline vessels (Table 1). It is preferable to obtain estimates from a survey, because fishery-dependent information can be heavily biased due to targeting or gear selectivity (Ricker, 1969).

There has been a resurgence of efforts to quantify spatial growth variability for several managed species, including Gulf Sheepshead (Adams et al., 2018) and northern rock sole (Hurst and Abookire, 2006), as well as sablefish (James et al., 2002; Mason et al., 1983). Though a robust volume of survey data is available for this species for all management regions, researchers have not yet analyzed available length and age data for the entire sablefish range for evidence of spatial patterns. The objective of this study was to investigate variation in growth rates for sablefish across the Northeast Pacific while minimizing the use of pre-supposed spatial stratifications in the analytical approach. We present the results of this evaluation with the intention of informing future sablefish modeling work in the northeast Pacific.

# Methods

We used simulation to explore the robustness of a new, data-driven approach to detect spatio-temporal breaks in fish growth. The modeling workflow was designed to identify significant spatiotemporal break-points in the age-length relationship and did not consider *a priori* hypotheses of spatial stratification. We employed a Generalized Additive Model (GAM) with smooth functions for latitude and year using the mgcv package (Wood, 2011) in R (R Development Core Team, 2011). The first derivatives of the GAM were evaluated to identify areas of significant change (i.e., break points) in growth parameter estimates.

The method involves fitting a GAM with the vector of observed lengths as the response variable, predicted by separate smoothers for year and latitude. Non-smoothed predictors included age (in years) and sex (male/female only; fish of “unknown” sex were removed from the analysis beforehand) so that the smooth functions represented all variation not explained by these factors.

Once the best-fit model was identified, we used the method of finite differences (as in Simpson, 2018) to locate time periods and/or locations of statistically significant change in growth. The finite differences approach approximates the first derivative of the spline generated from the GAM function. We calculated uncertainty in derivative estimates by computing the sum of the square root of the fixed-effects covariance matrix. We then identified years or latitudes where the confidence interval of the first derivative was outside the 5th to 95th percentiles of the entire dataset and designated these as “break points”. Once identified, we re-aggregated the raw length and age data to match these breakpoints and estimated the parameters of the VGBF using maximum likelihood in Template Model Builder (Kristensen et al., 2016). This was performed separately for each sex.

The VBGF is parameterized by *L∞* (asymptotic length), *k* (the rate at which asymptotic length is approached) and *t0* (the estimated age at length zero). The prediction for length at age is subject to an error term ε that is assumed to be lognormally distributed with zero mean and variance σ. Our model estimates values for the three biological parameters at each spatiotemporal strata for two sexes; the additive error term is assumed universal across strata and sex and normally distributed with mean zero.

Equation 1

2)

Initial parameters were t0 = 0, = 0, with L∞ = 70, K = 0.

## Simulation Testing

To evaluate the robustness of the proposed method, we performed a simulation study using datasets artificially generated via an individual-based model (IBM). The IBM is capable of mimicking individual characteristics by following the life history processes (survival, growth, and reproduction) of individual fish. Temporal variation in fish growth is achieved by changing the mean fishing mortality (*F*) experienced by the population with a generated vector of *F* as in (Carruthers et al. (2012). In this approach, we specify the median *F* for the final 50 years of the 100-year simulation; fish are only subject to natural mortality for the first 50 years. The median values for either the entirety or a subset of the final 50 years were either low (*F* = 0.15), medium (*F* = 0.25), or high (*F* = 0.35). We simulate spatial variation by generating length and age datasets under different growth regimes (i.e., higher values of K and ) and assign a range of latitudes to each regime. The growth module of the IBM itself implements a VBGF with L1 and L2 as in Stock Synthesis (Methot and Wetzel, 2013):

Equation =

Where represents the length of a fish at age , and K is the same as in Equation 1. An individual fish’s growth increment is updated using this computed and a bias-corrected lognormal error term. Depending on the scenario, the different regimes are either assigned completely distinct latitudinal ranges or ranges with some overlap.

The simulated scenarios described below were designed to represent the spectrum of possible growth regimes. The method was evaluated based on a) if it was able to accurately detect the presence or absence and location of a ‘break point’ in space or time, and b) if re-aggregation of the data at the proposed break point resulted in VBGF parameter estimates which overlapped with the true values used to generate the dataset.

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| --- | --- | --- |
| **Scenario Description** | **Fishing Mortality (Temporal Component)** | **Spatial Stratification** |
| No spatial or temporal breaks | Medium for all years | Latitude is uniform random variable for all points |
| *Temporal breaks* | | |
| Single, symmetrical temporal break with strong change | Low from years 1-24; high from years 25-100 and vice versa | Latitude is uniform random variable for all points |
| Single, symmetrical temporal break with weak change | Low from years 1-24; medium from years 25-100 (and vice versa); high from years 1-24; medium from years 25-100 (and vice versa) | Latitude is uniform random variable for all points |
| Three stages of temporal change | All permutations of low, medium, high in three roughly equal blocks | Latitude is uniform random variable for all points |
| *Spatial Breaks* | | |
| Single, symmetrical spatial break with no overlap | Medium for all years | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[25,50] for Regime 2 |
| Single spatial break with some overlap | Medium for all years | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[20,50] for Regime 2 |
| Spatial expansion/contraction | Medium for all years | Regime 1 Latitude ~ U[1,50] in year one, and moves ‘northward’ one degree each year. In year 50, Regime 2 ~ U[1,49] and Regime 1 ~ U[49,50] |
| *Combined Breaks* | | |
| Single, symmetrical temporal and spatial breaks with strong change, no overlap | Low from years 1-24; high from years 25-100 and vice versa | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[25,50] for Regime 2 |
| Single, symmetrical temporal and spatial breaks with weak change, no overlap | Low from years 1-24; medium from years 25-100 (and vice versa); high from years 1-24; medium from years 25-100 (and vice versa) | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[25,50] for Regime 2 |
| Single, symmetrical temporal and spatial breaks with strong change, some spatial overlap | Low from years 1-24; high from years 25-100 and vice versa | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[20,50] for Regime 2 |
| Single, symmetrical temporal and spatial breaks with weak change, some spatial overlap | Low from years 1-24; medium from years 25-100 (and vice versa); high from years 1-24; medium from years 25-100 (and vice versa) | Latitude ~ U[0,25] for growth Regime 1; Latitude ~ U[20,50] for Regime 2 |

Table . Summary of simulated datasets used to test method in presence/absence of spatio-temporal variation in growth. Regime 1 refers to a central Pacific billfish-like species, where Linf = 220 and K = 0.258; Regime 2 Linf = 350, K = 0.45.

## Application to Northeast Pacific Sablefish

We obtained fishery-independent length and age data from the Bering Sea and West Coast trawl surveys conducted annually by the National Oceanic and Atmospheric Administration. We also obtained length and age records from the Canadian Department of Fisheries and Oceans, which has performed an annual trap-based survey since 1991. Data from each region included measured length, sex, age, and the starting latitude and longitude which determined the survey station. Due to computational constraints, and to avoid disproportionate influence of more heavily-sampled regions, we randomly subsampled 8,239 records from each of the three management regions.

In constructing the GAM, we investigated the use of an AR1 temporal structure with lags of 1 to 3 years, but these models did not improve AICc over the initial model without autoregressive structure.

Once the best-fit model was identified, we used the method of finite differences (as in Simpson, 2018) to locate time periods and/or locations of statistically significant change in growth. The finite differences approach approximates the first derivative of the spline generated from the GAM function. We calculated uncertainty in derivative estimates by computing the sum of the square root of the fixed-effects covariance matrix. We then identified years or latitudes where the confidence interval of the first derivative was outside the 5th to 95th percentiles of the entire dataset and designated these as “break points”. Once identified, we re-aggregated the raw length and age data to match these breakpoints and estimated the parameters of the VGBF using maximum likelihood in Template Model Builder (Kristensen et al., 2016). This was performed separately for each sex.

The VBGF is parameterized by *L∞* (asymptotic length), *K* (the rate at which asymptotic length is approached) and *t0* (the estimated age at length zero). The prediction for length at age is subject to an error term ε that is assumed to be lognormally distributed with zero mean and variance σ. Our model estimates values for the three biological parameters at each spatiotemporal strata for two sexes; the additive error term is assumed universal across strata and sex and normally distributed with mean zero.

Equation 3

2)

We executed a maximum of 1000 iterations. Initial parameters were t0 = 0, = 0, with L∞ = 70, K = 0.

# Results

Our best-fit GAM produced a positive definite Hessian and converged after 10 iterations. It explained 42.4% of deviance. The latitude smoother suggested a generally increasing cline in length at age with latitude, with a significant breakpoint centered around 49˚N (approximately Vancouver, Canada), which corroborates results in Gertseva et al. (2017). The temporal smoother did not exhibit a strong one-way trend, though the quantile analysis identified a significant change in slope centered on years 2004-2005 (Figure 3). We therefore split the data collected during or after 2005 (hereafter referred to as “late”; prior data is “early”) and at 49˚N (hereafter referred to as “north”; data collected south of this point is designated as “south”). Parameter estimation in TMB for the VBGF generated estimates for mean and standard deviations of *t0*, log(*k*) and log(*L∞*) for unique combinations of north/south, early/late and male/female populations, and associated predictions for length at age (Figure 4). The error term was estimated to be 6.13 (standard deviation = 0.027). Across spatiotemporal strata and sexes, there was considerable overlap in parameter estimates for the growth rate *k,* whereas *L∞* and its confidence intervals were spread out at the stratification indicated by the GAM derivative analysis (Figure 5).

# Discussion

It is evident from this and previous work that there is some level of variation in sablefish growth, whether in the growth rates themselves or the spatiotemporal scale at which growth anomalies occur. Mis-specification of growth within stock assessment can overestimate management quantities, particularly the estimate of stock depletion (Stawitz et al., in prep). Correctly-specified growth variation in the estimation model can reduce uncertainty by correctly attributing process error to somatic growth anomalies. The purpose of this study was to define the ideal spatiotemporal scale at which to structure growth for future use in a range-wide operating model of sablefish population dynamics.

Previous work with sablefish data has utilized an *a priori* approach, wherein length data were aggregated into pre-hypothesized spatial zones and compared via Akaike’s Information Criterion. This ‘information-theoretic’ (Guthery et al., 2003) approach is fairly straightforward computationally, and has been implemented separately for the California Current (Gertseva et al., 2017) and Alaska federal and state sablefish fisheries (Echave et al., 2012; McDevitt, 1990). The CC analysis identified a statistically significant break in von Bertalanffy growth parameters for sablefish at approximately 30 degrees N, between Point Conception and Monterey, CA, with additional evidence for an increasing cline in L∞ with increasing latitude. That work also observed an increase in *k* estimates for populations sampled in the Vancouver region (ca. 49˚N), which was posited to be the result of samples coming from the “southern end of a faster-growing northern stock”, a suggestion supported by our findings. The authors of that study described how sablefish have been shown to highly migratory, with ontogenetic movements off the coastal shelf; such combined, complex life patterns could yield higher growth rates in northern regions that interact with a more generalized shelf-slope pattern observed in groundfish overall. For Alaska, a generalized linear model of length as a function of pre-specified zones and time blocks was used to diagnose a ‘regime change’ in sablefish growth occurring in year 1995, though the authors explain this shift is possibly attributable to changes in sampling strategy that occurred in that year’s survey. In the recent AK sablefish assessments, the parameters of the VBGF are time-blocked accordingly (see Table 1) despite caution that it the change is not inherent to the population, but likely an artifact of sampling methods. In our analysis (which included data for all regions), the first derivative was not zero in 1995 though it was not of enough magnitude to pass the quantile filter. **[Further discussion of sablefish movement following tagging analyses by Luke Rodgers, DFO postdoc].**

The consideration of temporal variation in sablefish growth is further complicated by the exploitation history of the fishery, which has steadily marched north- and west-ward over the last several decades, encountering ‘larger’ fish with subsequent expansion (M. Haltuch, pers. comm.). This suggests that differences in mean length across the region could be attributable to different degrees and durations of fishing pressure, and not inherent population differences alone. Importantly, the L∞ estimates for both sexes and regions show a decline from the ‘early’ to ‘late’ periods, resulting in nearly equivalent values for north and south regions for females and males, respectively. Simulation work by Stawitz et al. (2015) sought to model growth anomalies in sablefish (among other groundfish) as a process driven by variation in either annual, initial size or among cohorts. Data was partitioned between the CC and two regions of Alaska, and it was determined that annual-scale anomalies were more pronounced in the CC whereas the initial normalized length within each cohort explained more variation in Alaska. A principal conclusion was that the form of growth variation differed among ecosystems, wherein the CC is a more climactically variable region, which could explain why annual deviates were best for fitting to this data. Such ecosystem-driven trends may be diluted when analyzing the data as a composite, as in our study; notably, our temporal smoother did not produce a distinct annual cyclic trend. Methods that consider the space and time components co-dependently (as in vectorized auto-regressive spatio-temporal models, Thorson, 2019) may strengthen the ability to disentangle such trends, and also to consider spatial effects beyond simple latitude (e.g. near- and offshore).

# Figures

Figure 1. Histogram of raw length data from three regional surveys, colored by sex.



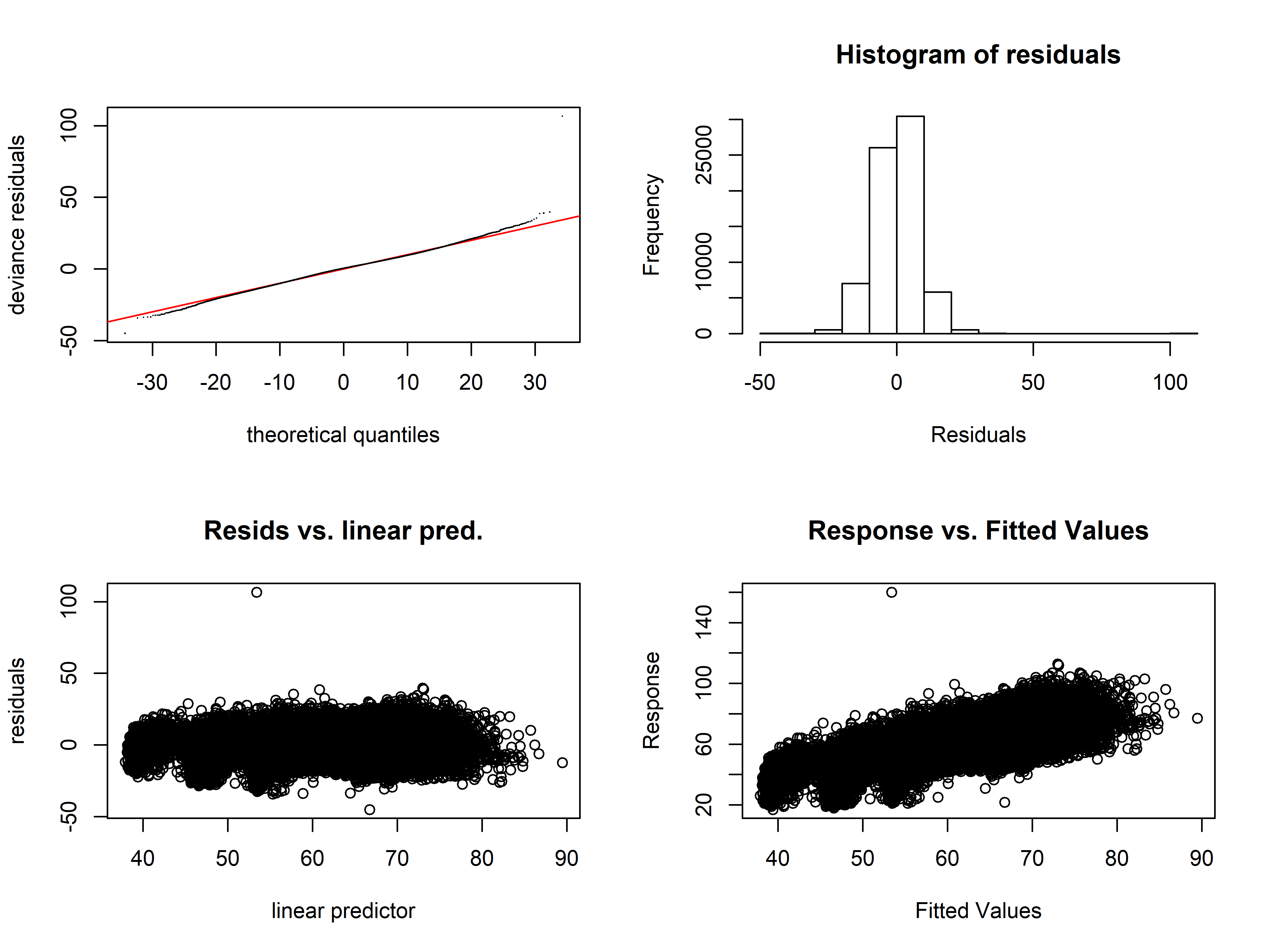


Figure 2. Diagnostic plots of best-fit GAM model. Clockwise from top left: quantile-quantile plot of deviance residuals; histogram of residuals; observed response values (lengths, in cm) vs predicted values, and model-predicted residuals vs linear predictor.

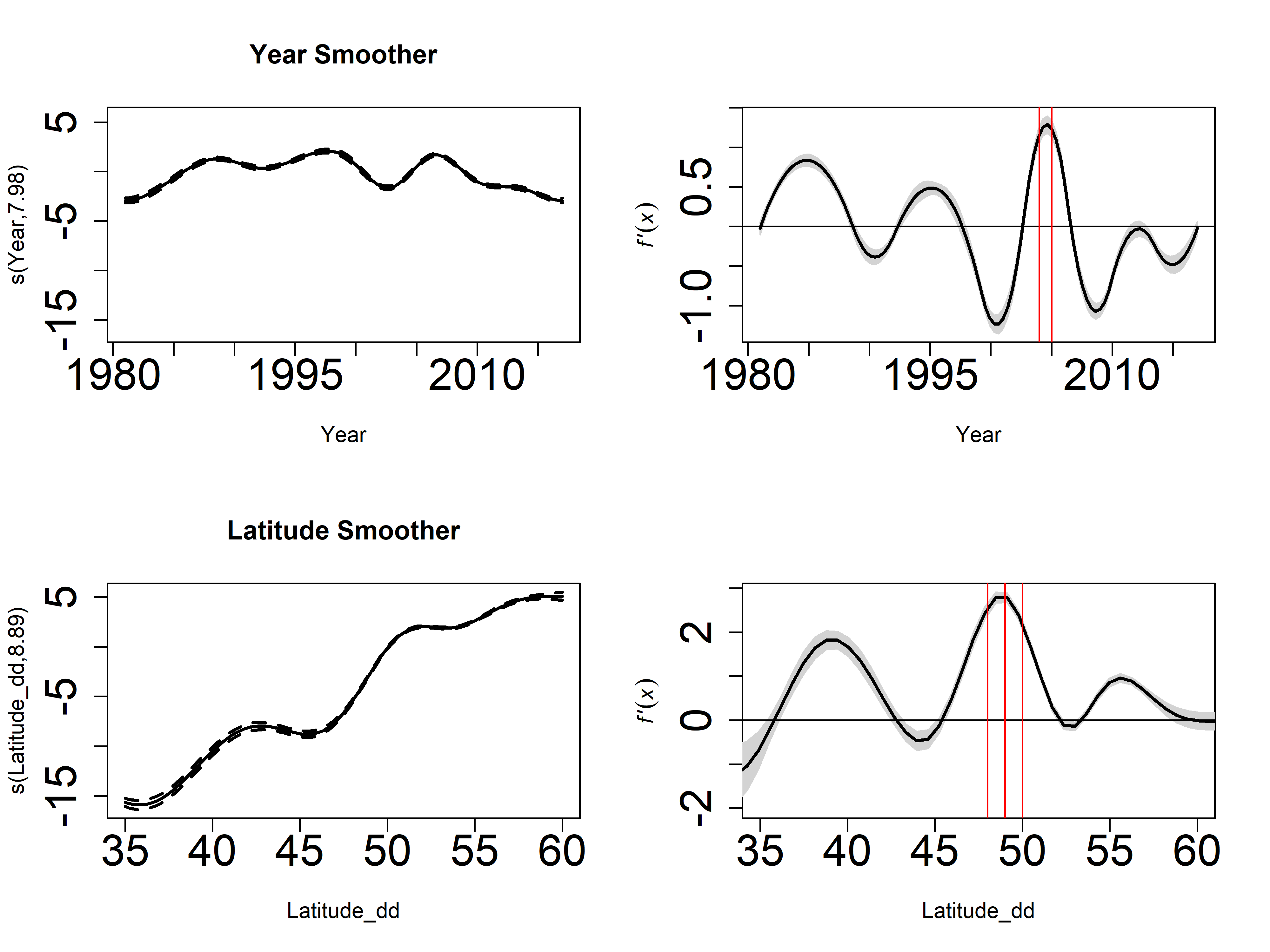


Figure 3. Plots of smoothers for Year and Latitude, and first derivatives thereof. Red lines indicate years or latitudes where the value of the first derivative was outside of the 95th percentile of values in the dataset.



Figure 4. Fits of von Bertalanffy growth function to data stratified at values determined using the derivative analysis of the GAM. Panels marked “early” are data obtained prior to 2005; “Northern” datapoints were collected north of 45˚N latitude. Predicted values are color-coded by sex.



Figure 5. Comparative boxplot of estimated parameters from spatiotemporally stratified data. The error term (not shown) was estimated universally for all regions and sexes.

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| **Region** | **Survey Method** | **Sample size used in this analysis** | | **VBGF parameters from recent assessments** | | | | | |
| **M** | **F** | **L∞** | | **K** | | **t0 (years)** | |
| **M** | **F** | **M** | **F** | **M** | **F** |
| West Coast of US (Johnson et al., 2015) | Trawl on chartered commercial fishing vessels | 4056 | 4183 | 57 | 64 | 0.41 | 0.32 | 0 (fixed) | 0 (fixed) |
| British Columbia | Stratified trap survey | 3725 | 4514 | 68.99 | 72.00 | 0.29 | 0.25 | 32.50 | 32.50 |
| Alaska Federal (Hanselman et al., 2015) | Longline on chartered commercial fishing vessels | 3531 | 4551 | \*67.8  ⁑65.3 | \*80.2  ⁑75.6 | \*0.29  ⁑0.28 | \*0.22  ⁑0.21 | \*⁑2.27 | \*⁑1.95 |

# Tables

Table 2. Overview of survey methods, data available and most recent VBGF parameters used for sablefish in stock assessments. \*Time-blocked VBGF parameters for AK Federal assessment 1996-current; ⁑Time-blocked VBGF parameters from 1960-1995 (Hanselman et al., 2017).

\*The WC assessment, which is written in Stock Synthesis, does not specify L∞ nor t0, but instead an age-length key (with values for minimum and maximum length and ages). Values were back-converted for presentation here.

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| --- | --- | --- |
| Predictor | Estimated Degrees of Freedom | Proposed Breaks |
| s(Year) | 7.984 | 2004, 2005 |
| s(Latitude) | 8.888 | 48˚ to 50˚N |

Table 3. Description of smoothers and values along each where the first derivative lay outside the 5th to 95th percentile.

# References

Adams, G.D., Leaf, R.T., Ballenger, J.C., Arnott, S.A., McDonough, C.J., 2018. Spatial variability in the growth of Sheepshead (Archosargus probatocephalus) in the Southeast US: Implications for assessment and management. Fish. Res. 206, 35–43. https://doi.org/10.1016/j.fishres.2018.04.023

Carruthers, T.R., Walters, C.J., McAllister, M.K., 2012. Evaluating methods that classify fisheries stock status using only fisheries catch data. Fish. Res. 119–120, 66–79. https://doi.org/10.1016/j.fishres.2011.12.011

Echave, K.B., Hanselman, D.H., Adkison, M.D., Sigler, M.F., 2012. Interdecadal Change in Growth of Sablefish (*Anoplopoma fimbria*) in the Northeast Pacific Ocean. Fish. Bull. 110, 361–374.

Gertseva, V., Matson, S.E., Cope, J., 2017. Spatial growth variability in marine fish: Example from Northeast Pacific groundfish. ICES J. Mar. Sci. 74, 1602–1613. https://doi.org/10.1093/icesjms/fsx016

Guthery, F.S., Burnham, K.P., Anderson, D.R., 2003. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. J. Wildl. Manage. https://doi.org/10.2307/3802723

Hanselman, D.H., Heifetz, J., Echave, K.B., Dressel, S.C., Jech, J.M., 2015. Move it or lose it: movement and mortality of sablefish tagged in Alaska. Can. J. Fish. Aquat. Sci. 72, 238–251. https://doi.org/10.1139/cjfas-2014-0251

Hanselman, D.H., Lunsford, C.R., Rodgveller, C.J., 2017. Assessment of the sablefish stock in Alaska in 2017. Stock Assess. Fish. Eval. Rep. Groundf. Resour. Gulf Alaska 576–717.

Hanselman, D.H., Lunsford, C.R., Rodgveller, C.J., 2015. Assessment of the sablefish stock in Alaska. Stock Assess. Fish. Eval. Rep. Groundf. Resour. Gulf Alaska 2014, 576–717.

Hurst, T.P., Abookire, A.A., 2006. Temporal and spatial variation in potential and realized growth rates of age-0 year northern rock sole. J. Fish Biol. 68, 905–919. https://doi.org/10.1111/j.0022-1112.2006.00985.x

James, M.K., Armsworth, P.R., Mason, L.B., Bode, L., 2002. The structure of reef fish metapopulations: modelling larval dispersal and retention patterns. Proc. Biol. Sci. 269, 2079–2086. https://doi.org/10.1098/rspb.2002.2128

Jasonowicz, A.J., Goetz, F.W., Goetz, G.W., Nichols, K.M., 2017. Love the one you’re with: genomic evidence of panmixia in the sablefish ( *Anoplopoma fimbria* ). Can. J. Fish. Aquat. Sci. 74, 377–387. https://doi.org/10.1139/cjfas-2016-0012

Johnson, K.F., Rudd, M.B., Pons, M., Akselrud, C.A., Lee, Q., Haltuch, M.A., Hamel, O.S., 2015. Status of the U.S. sablefish resource in 2015.

Kristensen, K., Nielsen, A., Berg, C., Skaug, H., Bell, B., 2016. TMB: Automatic Differentiation and Laplace Approximation. ournal Stat. Softw. 70, 1–21. https://doi.org/10.18637/jss.v070.i05

Mason, J.C., Beamish, R.J., McFarlane, G.A., 1983. Sexual Maturity, Fecundity, Spawning, and Early Life History of Sablefish ( *Anoplopoma fimbria* ) off the Pacific Coast of Canada. Can. J. Fish. Aquat. Sci. https://doi.org/10.1139/f83-247

McDevitt, M., 1990. Growth Analysis of Sablefish From Mark-Recapture Data From the Northeast Pacific. University of Washington.

Methot, R.D., Wetzel, C.R., 2013. Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. Fish. Res. 142, 86–99. https://doi.org/10.1016/j.fishres.2012.10.012

Punt, A.E., 2003. The performance of a size-structured stock assessment method in the face of spatial heterogeneity in growth. Fish. Res. 65, 391–409. https://doi.org/10.1016/j.fishres.2003.09.028

R Development Core Team, R., 2011. R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing. https://doi.org/10.1007/978-3-540-74686-7

Ricker, W., 1969. Effects of size-selective mortality and sampling bias on estimates of growth, mortality, production and yield. J. Fish. Res. Board Canada. https://doi.org/10.1139/f69-051

Simpson, G.L., 2018. Modelling palaeoecological time series using generalized additive models. bioRxiv. https://doi.org/10.1101/322248

Stawitz, C.C., Essington, T.E., Branch, T.A., Haltuch, M.A., Hollowed, A.B., Spencer, P.D., 2015. A state-space approach for detecting growth variation and application to North Pacific groundfish. Can. J. Fish. Aquat. Sci. 72, 1316–1328. https://doi.org/10.1139/cjfas-2014-0558

Thorson, J.T., 2019. Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments. Fish. Res. https://doi.org/10.1016/j.fishres.2018.10.013

von Bertalanffy, L., 1957. Quantitative Laws in Metabolism and Growth. Q. Rev. Biol. https://doi.org/10.1086/401873

Wood, S.N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. J. R. Stat. Soc. Ser. B Stat. Methodol. https://doi.org/10.1111/j.1467-9868.2010.00749.x