A data-driven approach to evaluate spatial growth zonation, with application to NE Pacific Sablefish

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Keywords: growth, von Bertalanffy, stock assessment, sablefish, spatial

# Abstract

Renewed interest in the estimation of spatial variation in fish body size is a result of computing advances and the development of spatially-explicit management frameworks. However, many attempts to quantify spatial structure or the distribution of traits utilize *a priori* approaches, which involve pre-designated geographic regions and thus cannot detect unanticipated spatial patterns. This study presents a new, data-driven method which evaluates the first derivative of the spatial smoothing term of a generalized additive model to identify spatial breakpoints in fish length-at-age. We use simulation testing to illustrate the robustness of the method across a variety of spatially stratified age and length data, and apply it to survey data for Northeast (NE) Pacific sablefish (*Anoplopoma fimbria*). Results indicate that sablefish size-at-age appears to increase with latitude in the NE Pacific, which is consistent with work from the western United States; simulation testing illustrates the robustness of the method across a variety of scenarios related to spatially complex growth data, including strict boundaries, overlapping zones and changes at the extreme of the range. This method has the potential to improve detection of large-scale spatial patterns in fish growth, and aid in the development of spatially-structured population dynamics models.

# Introduction

Renewed interest in the development of spatially-explicit management frameworks (e.g. Thorson et al., 2015) and advances in computing power have motivated efforts to quantify spatial variability in fish size for managed species, including Gulf Sheepshead (Adams et al., 2018) and northern rock sole (Hurst and Abookire, 2006), as well as groundfish off the US West Coast (Gertseva et al., 2017; James et al., 2002; Mason et al., 1983). Understanding demographic variation of this key trait (somatic growth) can improve the precision of fisheries assessment (Punt, 2003; Stawitz et al., 2019).

Fish somatic growth rates are typically modelled using the von Bertalanffy growth function (VBGF, von Bertalanffy, 1957) or an alternative functional form, with parameters estimated using model-fitting procedures. The spatial resolution of the resultant estimates is necessarily predicated on the aggregation of the data, which is often defined by survey stratification and/or changes in sampling gear. For example, Alaska federal and state sablefish fisheries estimated separate VBGF parameters for two periods of survey data based on the *a priori* hypothesis that changes in survey gear type would affect fish growth estimates from survey data (Echave et al., 2012; Hanselman et al., 2017; McDevitt, 1990), and imposed a time block between which estimates of the growth curve parameters were actually quite similar (see Table 3). Even more sophisticated approaches that utilize hierarchical Bayesian methods to estimate latitudinal and regional effects on length- or weight-at-age require a design matrix of dimensions dictated by pre-supposed zones (Adams et al., 2018). Such approaches are useful within a rigid management context, but do not represent the underlying growth process explicitly, and preclude the discovery of spatially-structured trends in fish size that violate management boundaries.

Attempts to quantify spatial variation in somatic growth typically face a trade-off between superimposing previous beliefs about stock structure (as in the Alaskan example above) or generating purely descriptive models of trait ‘gradients’ across regions or time periods, without a clear method to define significant break points within them (refs). This presents a gap for scientists, who wish to develop population dynamics models that accurately represent the population structure of managed stocks. The ideal tool is a data-driven method that defines significant break points in fish size, which researchers can then use to aggregate and estimate parameters of somatic growth. Our method, which evaluates the first derivative of smooth functions from a generalized additive model (GAM), meets this objective in a simple, rapid computational framework. Researchers are likely already familiar with GAMs, and the method does not require the specification of multiple error structures nor the construction of spatial meshes, which can be computationally expensive when large (Thorson, 2019a). The analysis of first derivatives in GAMs for change-point analysis has recently used in terrestrial paleoecology (Simpson, 2018) and geophysics (Beck et al., 2018). The objective of this study was to develop a method for detecting change points in spatially structured fisheries growth data that minimizes the use of pre-supposed spatial stratifications. This method has the potential to improve detection of large-scale patterns in fish growth, and aid in the development of spatially structured population dynamics models. We use simulation to test the robustness of the method for age-length data of varied spatial complexity, and present a case study application to northeast (NE) Pacific sablefish (*Anoplopoma fimbria).*

Sablefish 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 population declines across the entire range during the past few decades have increased concern about the status of sablefish and interest in the causes of the downward trend. Traditionally, sablefish stock assessment and management has occurred independently at regional scales, namely Alaska (AK), British Columbia (BC), and the US West Coast in the California Current (CC), 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 that represents the spatial heterogeneity of sablefish throughout their range.

# Methods

## Method Summary

The method involves fitting a Generalized Additive Model (GAM) using the mgcv package (Wood, 2011) in R (R Development Core Team, 2011) to the vector of observed lengths of age-six fish as the response variable, predicted by separate smoothers for year, latitude, and longitude, i.e.

Equation 1

where µt represents the expected mean of fish length, which is a random variable of which we have *t* observations; the linear effects of latitude (), longitude () and year (), which are smooth functions. Latitude and longitude are fit as separate smoothers as the estimation of derivatives for a two-dimensional spline, and inference thereof, is too complex for the present application. *g* is an invertible, monotonic function that enables mapping from the response scale to the scale of the linear predictor, such as the natural logarithm. To simplify the analysis, we fit the GAM to a subset of each simulated datasets including only female fish of age six (thus precluding the need to control for age or sex).

The first derivatives of the GAM with respect to latitude and longitude are evaluated to identify areas of significant change (i.e., break points) in fish size, which is taken as a proxy for zonal differences in fish growth. The equations below provide an example using latitude , but the process is repeated for each smoother. The finite differences method (as in Simpson, 2018) approximates the first derivative of the spline generated from the GAM function. For instance, the vector of derivatives **G** for latitude is produced via the following (see Figures 2 and 3):

Equation 2

where is a vector of predicted lengths at latitudes , defined by the user as ( = 0.001 in this analysis) with other effects (year, longitude) held constant. Therefore, the numerator of **G** is the difference between the predicted and observed length over latitudinal interval , which is necessarily small. Vector **G** is of the same length of the observed dataset.

The uncertainty in derivative estimates are computed as:

Equation 3

where **V** is a 1x1 covariance matrix for each of parameters of the current GAM spline (typically just one); the square root provides the standard error for each derivative estimate of the spline. These steps are then repeated for years and longitudes for the data set at hand. For each parameter, we identify where the maximum absolute value of the first derivative is obtained; this is rounded to the nearest integer and defined as the “breakpoint” as long as its 95% confidence interval does not include zero. Figures 2 and 3 illustrate the raw data, smoothers and first derivatives thereof for two sample datasets. Once identified, the raw length and age data (including all ages of fish) are re-aggregated to match the breakpoints and the parameters of the VGBF (*L∞* - asymptotic length, *k* - the rate at which asymptotic length is approached and *t0* - the estimated age at length zero) estimated using maximum likelihood in Template Model Builder (Kristensen et al., 2016) under the assumption that the error is normally distributed with zero mean and variance σ.

Equation 4 2)

The growth curve was fitted separately for each sex, resulting in estimated values for the three growth parameters for each spatiotemporal stratum by sex; For all runs, initial parameters were *t*0 = 0.1, = 0.1, with *L*∞ = 150cm, *k* = 0.1. The estimation procedure also calculates the predicted length at the endpoints of the estimated growth curve (the length at a pre-specified minimum and maximum age, which were 0 and 15 years in our simulation). These values and their standard errors are used in the evaluation of the method (see Performance Metrics), as *L*∞ and *k* are typically negatively correlated.

## Simulation Testing

We performed a simulation study to evaluate the performance of the proposed method, using datasets generated using an individual-based model (IBM, see Appendix for full details). The IBM is capable of mimicking individual characteristics by following the life history processes (survival, growth, and reproduction) of individual fish. We simulate spatial variation by generating length at age datasets under different growth regimes (e.g. varied values of *K* and/or ) and assign a range of latitudes to each regime. The IBM implements the VBGF using Schnute’s (1981) formulation of the VGBF, which requires (*k*, *L*1, *L*2) so is computed as:

Equation 5 =

where represent the lengths of a fish at ages , , and *k* is the Brody growth parameter as before. An individual fish’s annual growth increment is subject to a bias-corrected lognormal error term. Depending on the scenario, different growth ‘Regimes’ (defined as distinct *k,* and/or values) are either assigned completely distinct spatial ranges or ranges with some overlap. To simulate spatial zones, fish locations were sampled from a uniform distribution with boundaries specific to a certain growth Regime. Regime 1 refers to a central Pacific billfish-like species, where *L*1 = 62.69, = 216.72cm and *k* = 0.258; in Regime 2, which was designed to be of high contrast compared with Regime 1, *L*1= 50cm, = 350cm and *k* = 0.45; in Regime 3, which was designed to be low-contrast compared to Regime 1, =50cm, and *k* = 0.3.

The simulation scenarios described in Table 1 were designed to represent a variety of possible regimes in spatial growth variation. In all except the final (break-at-edge, fifth row) and non-spatial scenarios, the latitude and longitude of fish grown under Regime 1 are sampled independently and at random from a uniform distribution between 0° and 25°; for simulations with spatial variation, fish grown under Regimes 2 and 3 have latitude and longitude sampled the same way from 25° to 50°. In the break-at-edge scenario, fish simulated under life history Regime 1 are assigned latitudes and longitudes sampled independently and at random from a uniform distribution from 1° to 49°, and those simulated under Regime 2 have coordinates sampled similarly with both latitude and longitude bounded from 49° to 50°. Under each scenario, we generated 100 replicate datasets, which averaged 439 age-six fish per dataset, and tabulated the frequency at which a given (true) break point was identified using the method described above. Our simulation scenarios did not explicitly test temporal changes in growth, though the GAM includes a temporal smoother which is likely of use in real-world fisheries.

## Performance Metrics

We examined two performance metrics for the method: 1) the proportion of simulations within each scenario which detected the correct spatial breakpoints, for which we tabulated the number of times each spatial simulation matched either latitude, longitude, or both, and 2) the coverage probabilities of the endpoints of the resultant estimated growth curve. For all but the scenario with overlapping ranges (Table 1, row 4), the GAM analysis must have detected the correct breakpoint exactly to have been counted as a match. For the scenario with overlapping ranges, the ‘true’ dataset contained fish grown under Regimes 1 and 2 in a shared region between 20° and 25° latitude and longitude; the breakpoint was counted as an accurate match if it fell within this range.

For each simulation, after aggregating into GAM-designated spatial zones and estimating the growth curve, we determined whether the 95% confidence interval of the estimated fish size at ages zero and fifteen (our and ) contained the true *L1* and *L2* values used in the IBM to generate fish from that region. For example, fish generated under Regime 1 and occupying latitudes and longitudes between 0° and 25° may have been re-aggregated via the GAM analysis into a *de facto* ‘Region’ ranging from 0° to 24° degrees, the parameters of the VBGF estimated, and the endpoints of the estimated curve compared to those from Regime 1.

## Application to Northeast Pacific Sablefish

We obtained fishery-independent length and age data from the Alaska Sablefish Longline Survey and the U.S. West Coast Groundfish Bottom Trawl Survey conducted annually by the Alaska Fisheries Science Center and Northwest Fisheries Science Center, respectively. 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 15,000 total records from each of the three management regions. This produced a data set with an average of 1315, 1283, and 65 age 4, 6 and 30 sablefish from each region.

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. We fit the GAM and used the first-derivative method to identify spatial and temporal breakpoints for each sex separately, and subset the data to explore breakpoint detection at several key ages: age 4 (before length-at-50%-maturity for both males and females in all regions), age 6 (after length-at-50%-maturity for both males and females in all regions) and age 30, roughly the length at which sablefish are expected to obtain their maximum size (Johnson et al., 2015). We then re-aggregated the data to match the breakpoints for which there was general agreement across these GAMs as well as an ecosystem-based breakpoint at 145°W. This latter breakpoint was determined by Waite and Mueter (2013) via cluster analysis to delineate unique regions of chlorophyll-a variability, which has been shown as nominally influential in the sablefish recruitment process (Shotwell et al., 2014) but by definition such an effect is not detectable in analysis of fish larger than recruits.

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.

# Results

## Simulation Study

The simulation study demonstrated that the first-derivative method was able to detect both spatial breakpoints correctly, and did so more frequently than erroneous locations for all spatial scenarios except two: one with low contrast between growth regimes, and another where the high-contrast spatial break occurred near the edge of the study region at 49° latitude and longitude. Figure 1 shows a map of an example data set for each of the scenarios presented in Table 1, and Figures 2 and 3 show smoothers and breakpoints identified for two sample datasets from two tested scenarios. Both Table 2 and Figure 4 indicate the coverage probabilities and proportion of simulations wherein the correct breakpoint was detected.

For all scenarios, the method obtained better coverage probability for the length at age zero (*L1*), at 96%-100% coverage for three simulations, and 55% percent in the scenario with overlap (Table 2). Coverage probabilities for length at age 15 (*L2*) were never over 33%. In terms of breakpoint detection, there was not a discernable difference in the method’s ability to correctly detect latitudinal vs. longitudinal breakpoints across scenarios, though it correctly detected both breaks most often in the overlapping scenario (0.99), followed by the scenario with a symmetrical, high-contrast break at 25° (0.75). For the scenario with zero breaks, it only correctly detected this to be case in 64% of simulations; there was no discernable pattern to the spurious breakpoints identified in the remaining 36%. The method was completely unable to detect the accurate breakpoints for the scenario with a spatial break at 49°, assigning the break at 50° latitude and longitude in 100% of simulations. The resultant coverage probabilities were uniformly zero, likely due to the high contrast in size-at-age between the two regions, which rendered estimates of the aggregated data uninformative.

## Application to NE Pacific Sablefish

For all ages examined, the latitude smoother suggested a generally increasing cline in length-at-age with latitude, with a significant breakpoint centered around 50˚N (approximately Vancouver, Canada) for both age four and six fish. Both age six and age 30 female sablefish identified a breakpoint of 36˚N (approximately Monterey, CA, USA)both of which corroborateresults in Gertseva et al. (2017). The temporal smoother did not exhibit a strong one-way trend, and was flat for age-30 fish of both sexes, though it did detect a break in 2009-2010 for both sexes of age 4 and 6 sablefishWe therefore split the data collected during or after 2010 (hereafter referred to as “late”; prior data is “early”) and into the five total regions defined by the detected breakpoints and the ecocystem-based break at 145˚W discussed above (see Figure 8). 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 regional, early/late and male/female populations, associated predictions for length at age (Figure 8). The error term across all regions and sexes 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 9).

# Discussion

## ADD: how much contrast really matters, reassuring that R3 performed best because this is likely scenario (gradient)

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## Simulation Study

On the whole, the model performed best for both performance metrics for the overlapping scenario (which had the advantage of being ‘matched’ whenever the breakpoint fell within 20° to 25°). The most commonly detected breakpoint in latitude and longitude for that scenario, before rounding, was the midpoint of this range (22.5°), which is likely an artifact of the penalization function within the GAM, which seeks to minimize curvature on either side of a given knot (i.e. breakpoint). The performance of the overlapping scenario was closely followed by the high-contrast break at 25°. Over 90% of all simulations correctly did not detect any temporal breakpoints, which was reassuring as growth was not made to vary across years.

We observed a failure of the method to detect breakpoints at the edges, with a true break at 49° consistently being assigned 50°. Such breakdown of detection methods at the margins of a series (at the edges of a study region, or at the end of a time-series) has been documented in Rodionov (2004). The same author developed a new method using sequential t-tests to perform such edge-case detection, which has been applied to detect ecosystem regime shifts in the Bering Sea. In terms of fisheries management, this suggests that managers may need alternative tools to detect and appropriately consider variations in growth at the extremes of their spatial domain, or regime shifts occurring at the present moment. However, multiple lines of evidence have suggested that somatic growth in fisheries follows ecosystem gradients (rather than management boundaries), and the ongoing emphasis on ecosystem-based fisheries management will hopefully involve the analysis of fish stocks at meaningful regional scales across which changes can be expected.

The method indicated tradeoffs between the accuracy of breakpoint detection and resultant coverage probabilities in the estimated growth curve, as well as large differences in the coverage probabilities of fish size at younger vs. older ages. It is encouraging that the approach could correctly detect breakpoints in the scenario with overlapping ranges of distinct fish growth, which is likely more similar to real-world fish populations (cite). However, the assigned ‘zonation’ of these populations necessarily combined fish with contrasting growth curves into a single dataset for estimation, and resulted in a loss in accuracy (coverage probability) for the endpoints of the growth curve. We suggest scientists use the method as a guidance tool to identify general zones between which growth could vary, and not take the detected breakpoint itself as the absolute truth. Importantly, suggestions of spatial breakpoints produced by the method should necessarily be considered in the context of the ecosystem, and prior knowledge of how the fishery at hand responds to features (e.g. temperature, depth) which may vary with latitude and/or longitude. Below, we discuss the results found during the application to northeast Pacific sablefish, with respect to ecosystem concerns.

### Caveats of Approach

One notable weakness of the GAM approach is the model’s sensitivity to the penalty function, often referred to as λ, which controls the degree of smoothness of the spline and, when unchecked, can lead to overfitting. Since the purpose of this analysis was diagnostic (the detection of where the spline is changing the most), we were able to avoid undue influence from this parameter by a) selecting only the maximum first derivative and b) disregarding values whose confidence interval contained zero, which was common in highly curved splines. Additionally, the fitting method could have been improved by either performing the spatial and temporal analyses in a stepwise fashion, or by re-aggregating the data to include an early and late stratum for each spatial zone. Finally, we did not consider movement of fish between regions, which could complicate the effectiveness of the method by observing fish “grown” under a separate regime into a new region. The method was able to detect changes within such mixed zones provided that there were other, more homogeneous areas in the study region.

## North Pacific Sablefish

The evaluation of size-at-age for NE Pacific sablefish was directly motivated by the notion that fish growth may vary at a scale different to the management boundaries.

Estimates of the parameters of the growth curve for sablefish are usually based on survey data acquired from chartered commercial trawl or longline vessels (Table 3). It is preferable to obtain estimated growth parameters using data from a survey, because fishery-dependent information can be heavily biased due to targeting or gear selectivity (Ricker, 1969).

It is evident from this and previous work (Echave et al., 2012; Gertseva et al., 2017; McDevitt, 1990) 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 lead to overestimation of management quantities, particularly the estimate of stock depletion (Stawitz et al., 2019). Correctly-specified growth in the estimation model can reduce uncertainty by correctly attributing process error to somatic growth anomalies..

Previous work with sablefish data has utilized an *a priori* method, wherein length and age data were aggregated into pre-hypothesized spatial zones and fitted VBGF curves were compared via Akaike’s Information Criterion. This ‘information-theoretic’ (Guthery et al., 2003) method 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 WC 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 found 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 be 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 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 3) despite caution that 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 WC and two regions of Alaska, and it was determined that annual-scale anomalies were more pronounced in the WC 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 WC 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

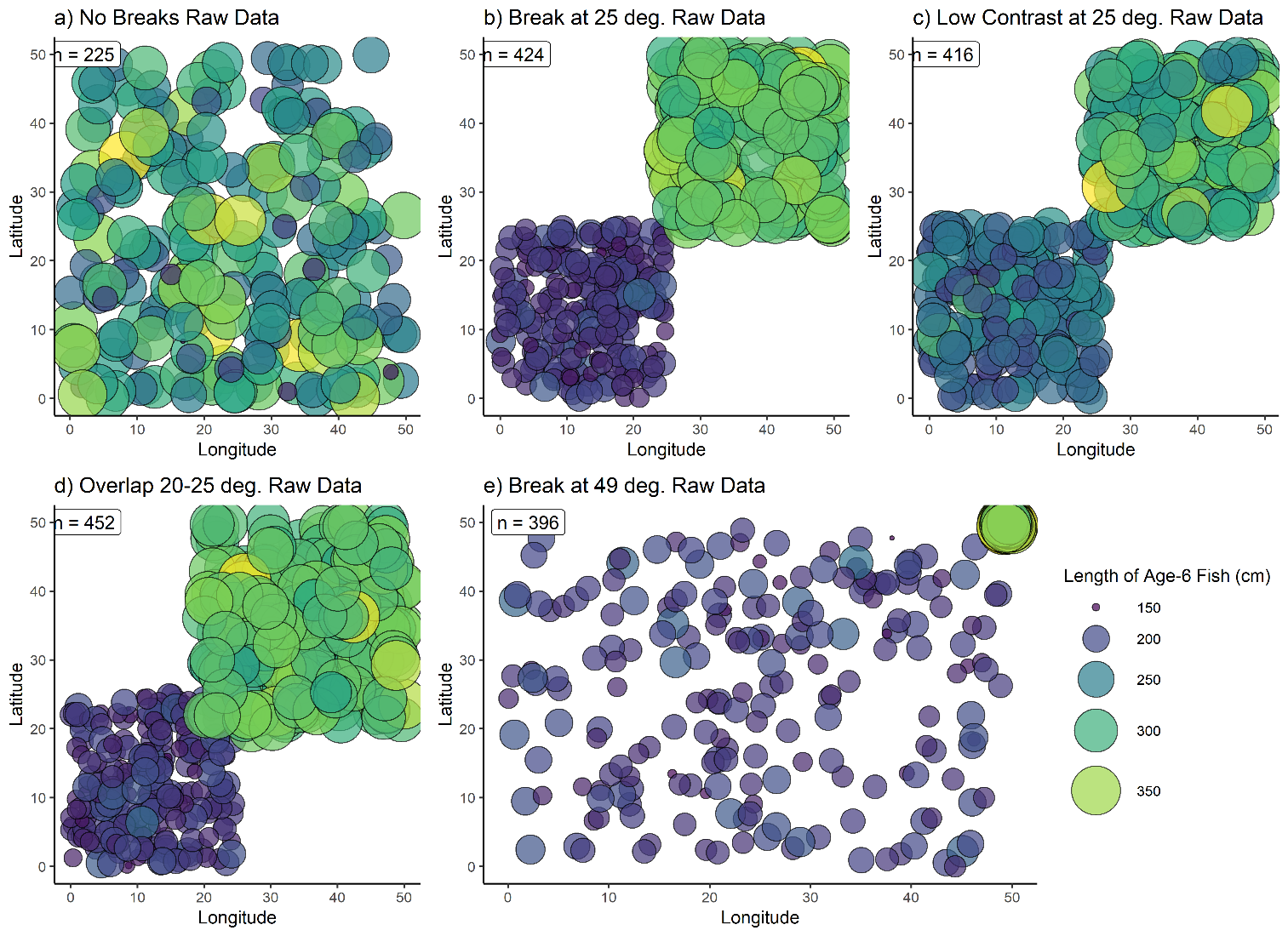


Figure 1. Example single dataset for each tested spatial scenario presented in Table 1. For each scenario, points represent the length and location of a single simulated fish of age six. Fish locations (latitudes and longitudes) were sampled from a uniform distribution of the boundaries indicated in Table 1. Text labels indicate the number of individual fish in the sample.

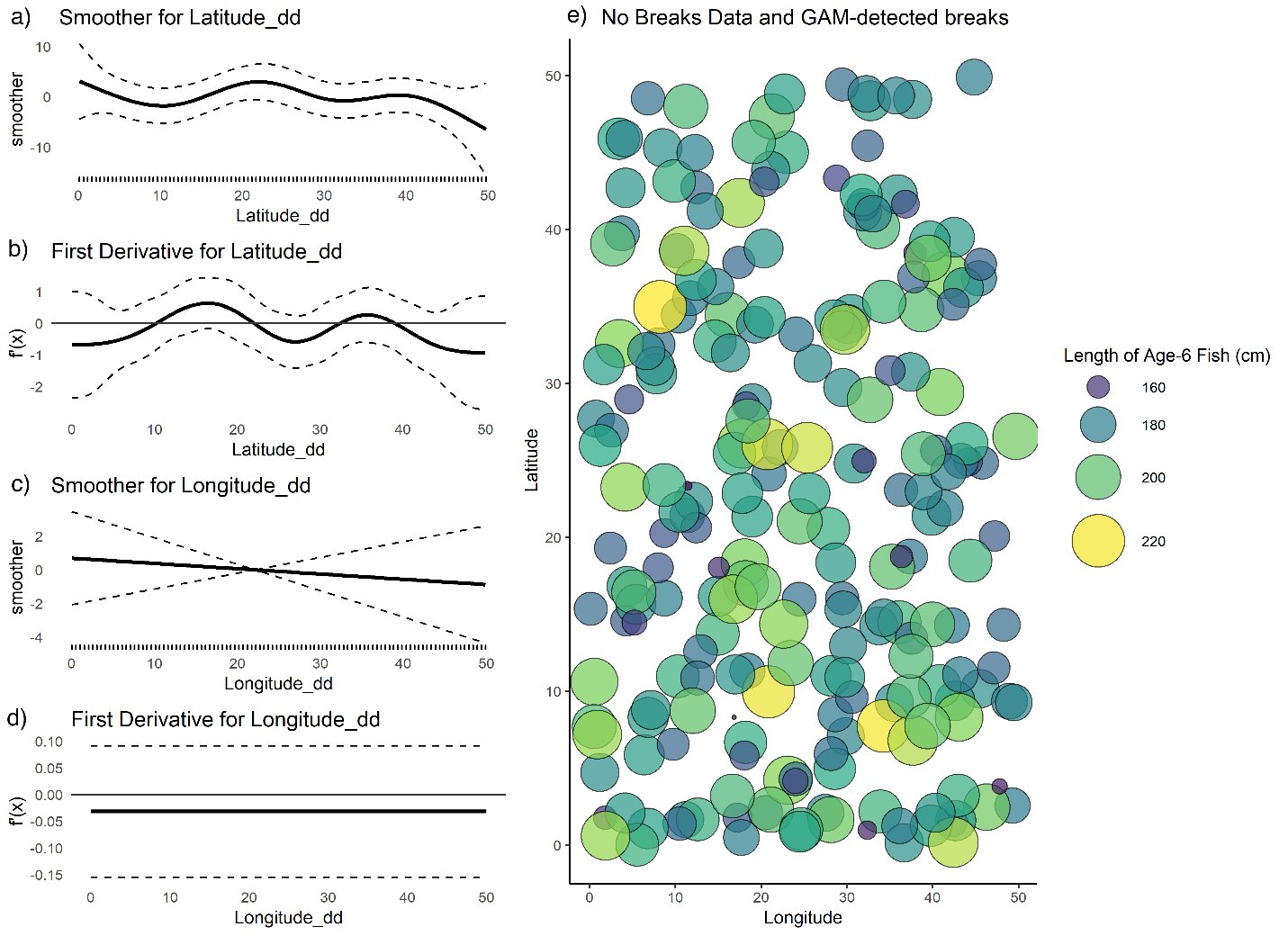


Figure 2. (a,c) raw value of GAM smoothers for Latitude and Longitude; (b,d) mean (black line) and 95% CI (dashed lines) of first derivative of the spatial smoothers; (e) map of age-6 fish for a single simulated dataset with no designated spatial breaks. No break points were detected by the GAM.

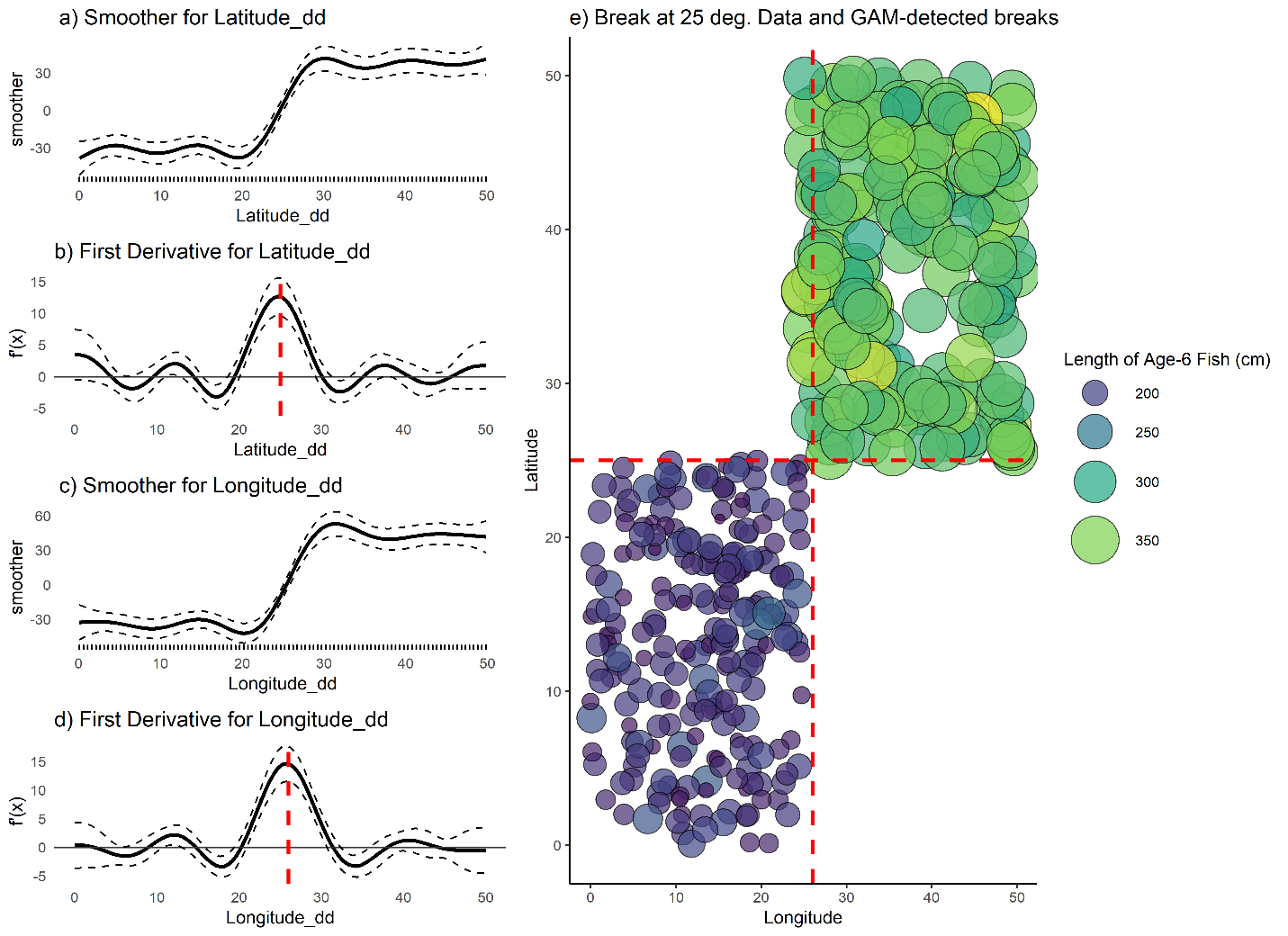


Figure 3. (a,c) raw value of GAM smoothers for Latitude and Longitude; (b,d) mean (black line) and 95% CI (black dashed lines) of first derivative of the spatial smoothers; (e) map of age-6 fish for a single simulated dataset with no designated spatial breaks. Vertical dashed red lines indicate detected break points, which are the maximum value obtained for this data set and may not have a confidence interval that contains zero.

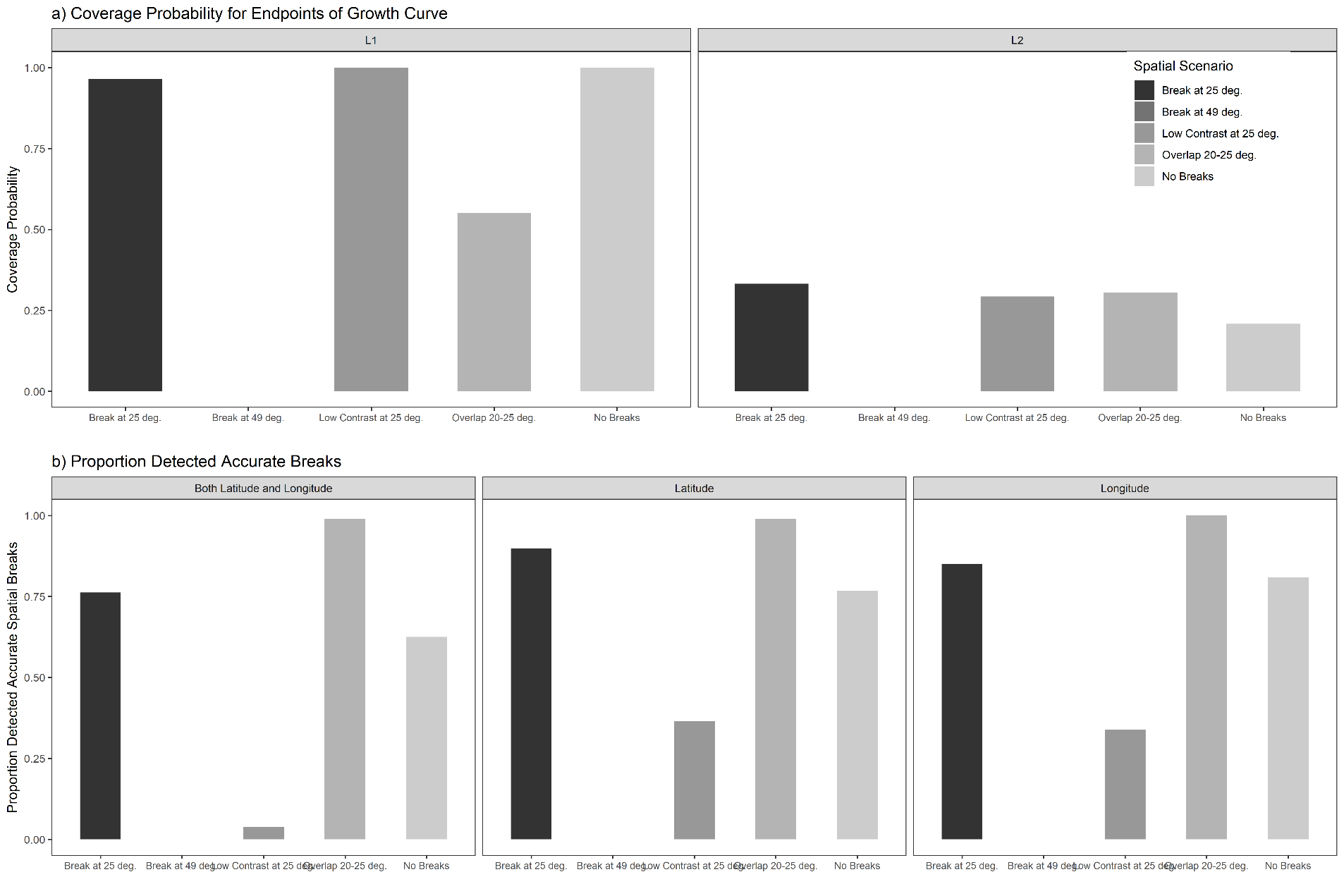


Figure . a) coverage probabilities for endpoints of growth curve, L1 (left) and L2 (right), and b) proportion of 100 simulations for each spatial scenario wherein the correct breakpoints (left), latitudinal breaks (center), or longitudinal breaks (right) were detected.

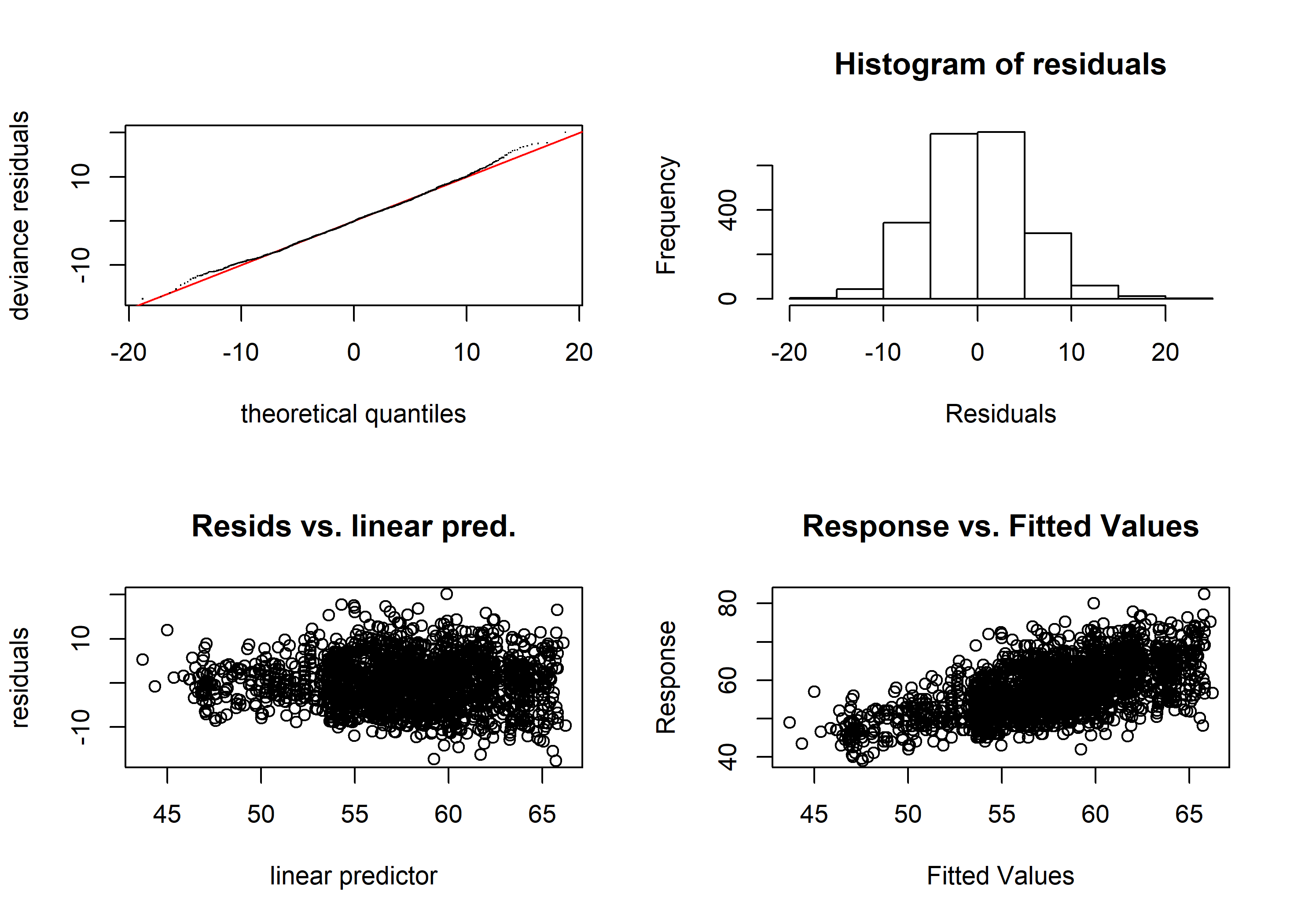


Figure 6. Diagnostic plots of best-fit GAM model for female age four sablefish. Clockwise from top left: quantile-quantile plot of deviance residuals; histogram of residuals; observed response values (lengths, in cm) vs predicted values, and model-predicted residuals vs linear predictor. See appendix for equivalent plots for other key ages and all sexes.

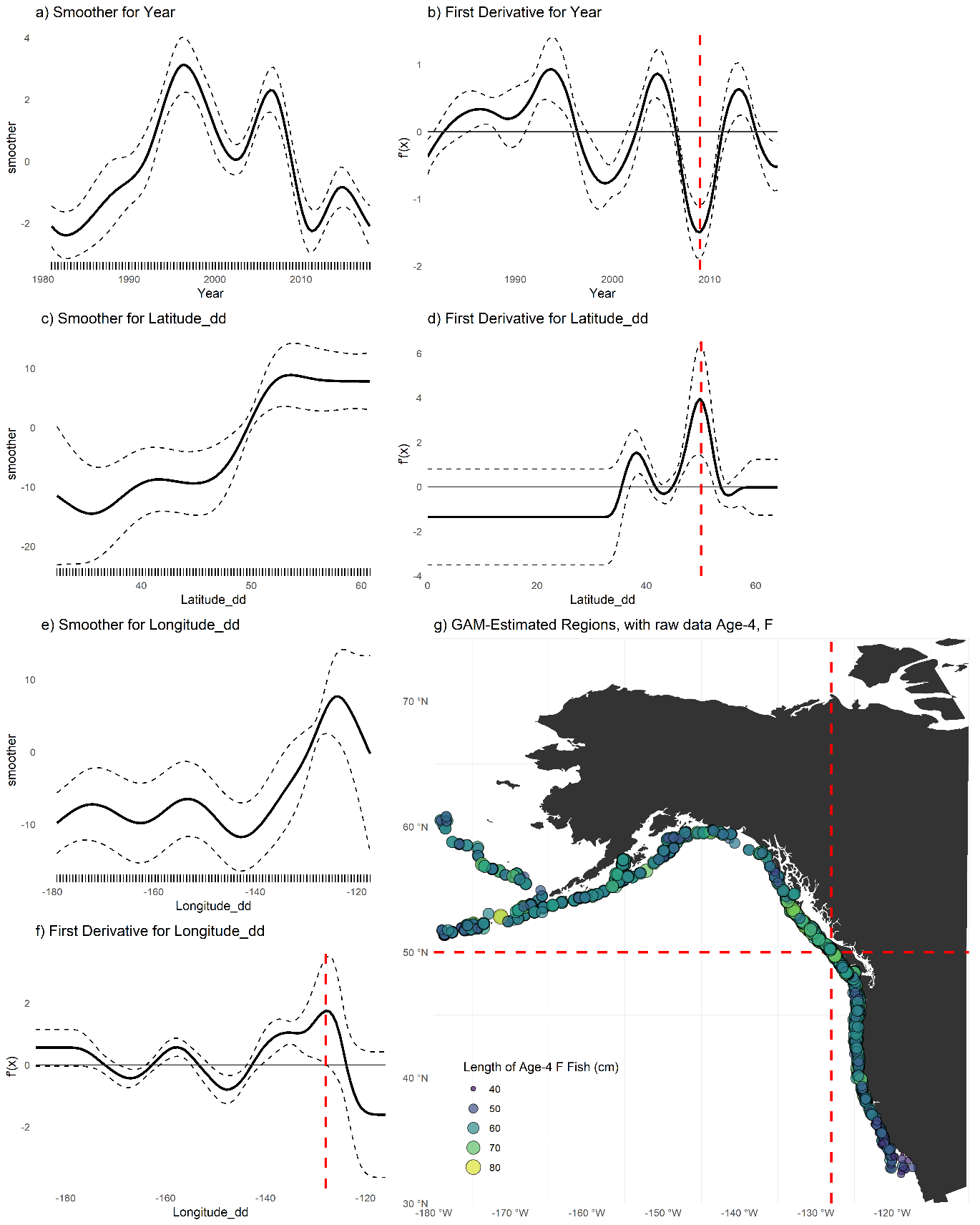


Figure 7. (a,c,e) Plots of smoothers for Year, Latitude, and Longitude, and first derivatives thereof for age-four female sablefish (b,d,f). Red lines indicate latitudes or longitudes that produced the highest first derivative and had a confidence interval that did not include zero.g) map with model-detected breakpoints (red lines). See appendix for similar plots for different key ages and sexes.

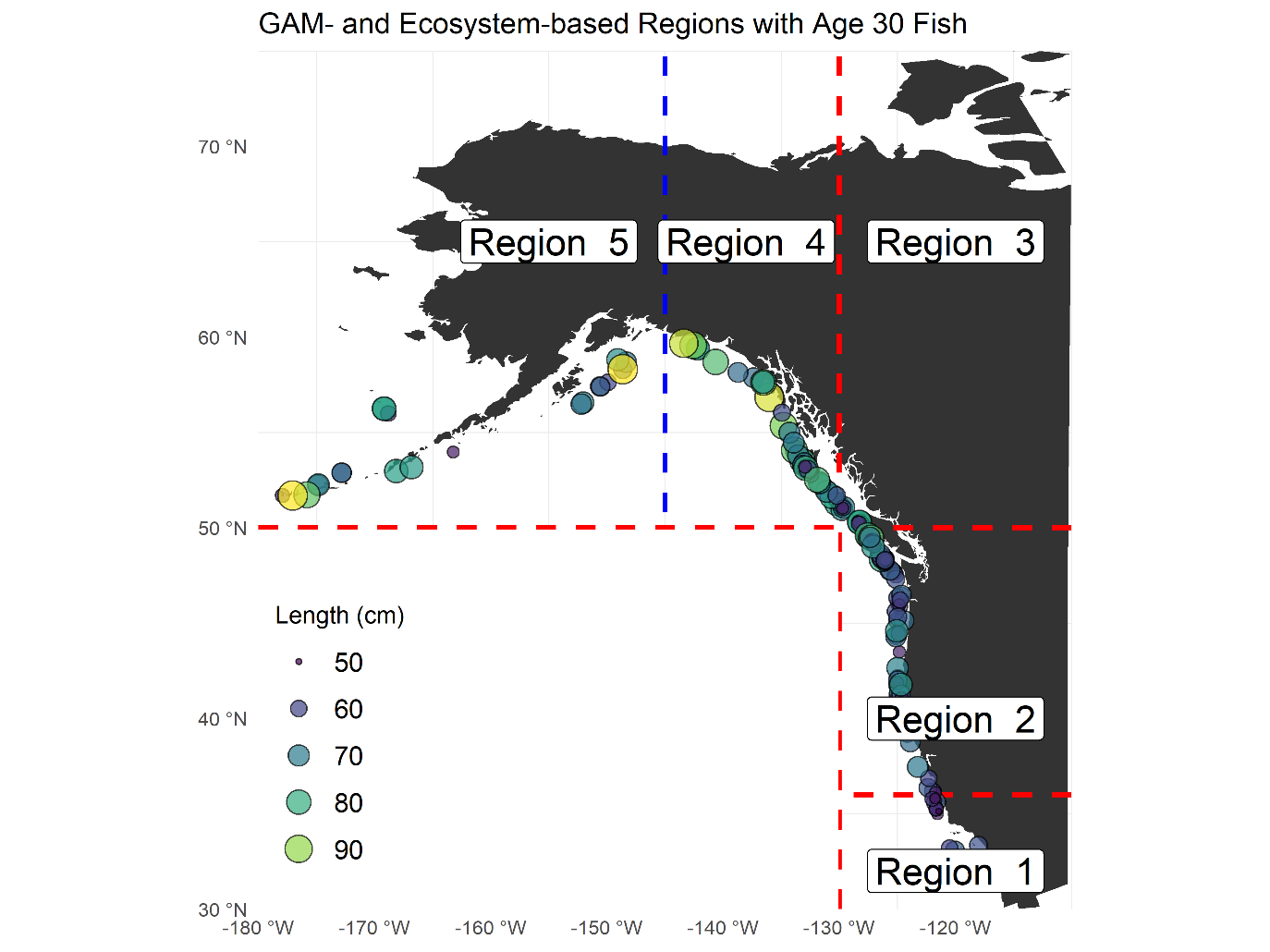


Figure 8. Method-detected breakpoints (red dashed lines) and ecosystem-based break (blue dashed lines) used to delineate growth regions for sablefish. For illustration, points are raw sablefish observations of both sexes at age 30 years

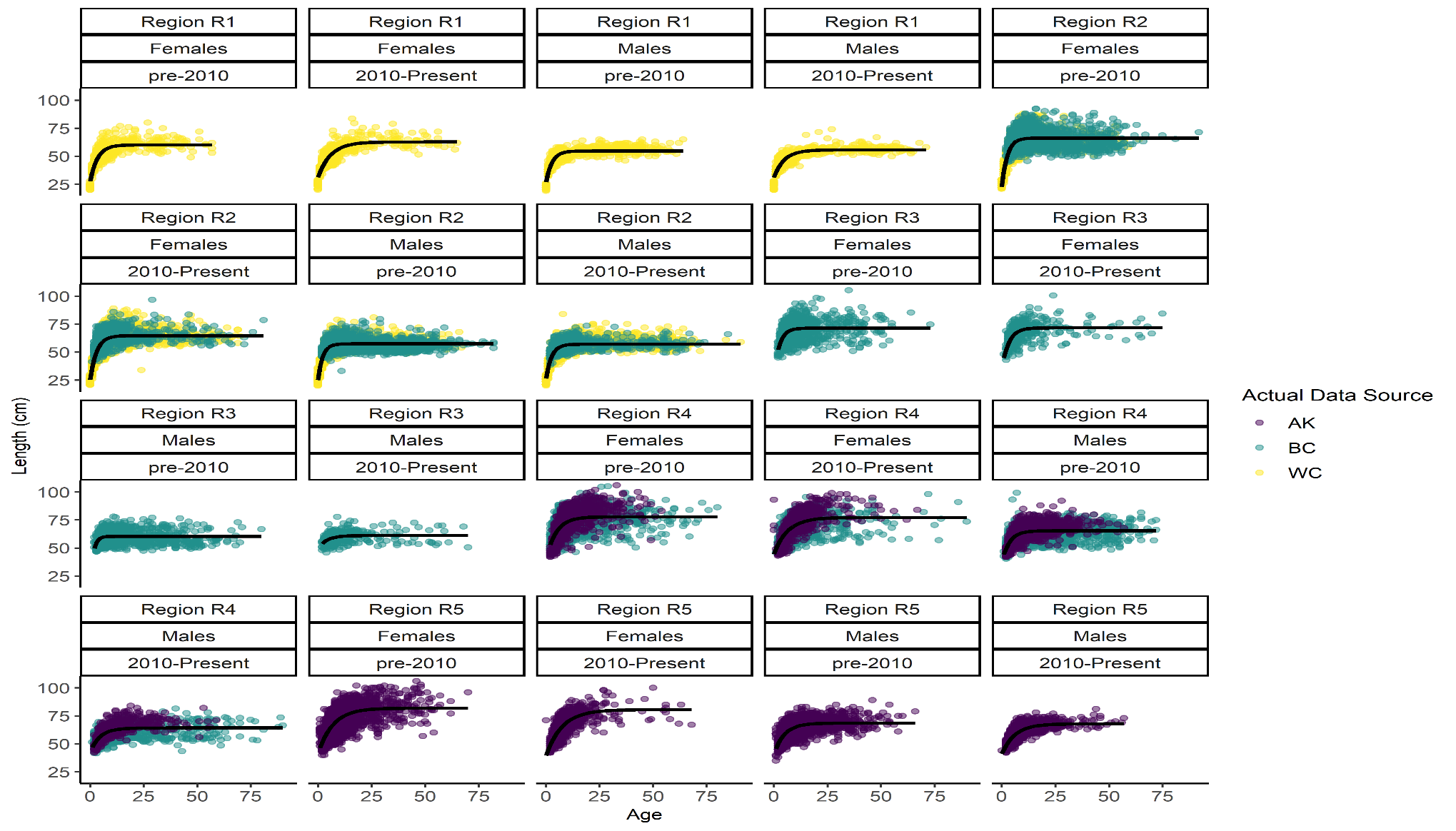


Figure 9. Fits of von Bertalanffy growth function to data stratified at values determined using the derivative analysis of the GAM. Panels marked “early” are data obtained prior to 2005; “Northern” datapoints were collected north of 45˚N latitude. Predicted values are color-coded by sex.

# Tables

|  |  |
| --- | --- |
| **Scenario Description** | **Spatial Stratification** |
| No spatial breaks | Latitude and Longitude ~ U[0,50], all fish under Regime 1 |
| Single, spatial break in middle of range, with no overlap and strong contrast | Latitude and Longitude ~ U[0,25] under growth Regime 1; Latitude and Longitude ~ U[25,50] under Regime 2 |
| Single, spatial break at 25 degrees with no overlap and reduced contrast | Latitude and Longitude ~ U[0,25] under growth Regime 1; Latitude and Longitude ~ U[25,50] under Regime 3 |
| Single spatial break with some overlap | Latitude and Longitude ~ U[0,25] under growth Regime 1; Latitude and Longitude ~ U[20,50] under Regime 2 |
| Single spatial break at edge of range with no overlap | Latitude and Longitude ~ U[0,49] under growth Regime 1; Latitude and Longitude ~ U[49,50] under Regime 2 |

Table 1. Summary of simulated datasets used to test the proposal method in presence/absence of spatial variation in growth.

|  |  |  |  |
| --- | --- | --- | --- |
| **Scenario Description** | **True Break Points** | **Coverage probability for L1, L2** | **Proportion correct latitude, longitude, both** |
| No spatial breaks | None | 1, 0.21 | 0.76, 0.80, 0.63 |
| Single, symmetrical spatial break in middle of range, with no overlap and strong contrast | 25° Latitude and 25° Longitude | 0.96, 0.33 | 0.90, 0.85, 0.76 |
| Single, symmetrical spatial break at 250 with no overlap and reduced contrast | 25° Latitude | 1,0.29 | 0.36, 0.33, 0.03 |
| Single spatial break with some overlap | 49° Latitude | 0.55, 0.305 | 0.99, 1, 0.99 |
| Single spatial break at edge of range with no overlap | Between 20° and 25° Latitude | 0, 0 | 0, 0, 0 |

Table 2. Summary of true and most-frequently detected break points following GAM derivative analysis, and coverage probabilities of the endpoints of the post-aggregation growth curves.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Region** | **Survey Method** | **Sample size used in this analysis** | | **VBGF parameters from recent assessments** | | | | | |
| **M** | **F** | **L∞ (cm)** | | ***k*** | | **t0 (years)** | |
| **M** | **F** | **M** | **F** | **M** | **F** |
| West Coast of US (Johnson et al., 2015) | Trawl on chartered commercial fishing vessels | 7778 | 7222 | 57 | 64 | 0.41 | 0.32 | 0 (fixed) | 0 (fixed) |
| British Columbia | Stratified trap survey | 6912 | 8088 | 68.99 | 72.00 | 0.29 | 0.25 | 32.50 | 32.50 |
| Alaska Federal (Hanselman et al., 2015) | Longline on chartered commercial fishing vessels | 6818 | 8182 | \*67.8  ⁑65.3 | \*80.2  ⁑75.6 | \*0.29  ⁑0.28 | \*0.22  ⁑0.21 | \*⁑2.27 | \*⁑1.95 |

Table 3. 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 for AK Federal assessment 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

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Region | Period | Sample Size used to fit gam | | Estimated VGBF Parameters | | | | | | Endpoints of growth curve | | | | |
| **L∞ (cm)** | | **k** | | **t0 (years)** | | L1 | | L2 | |
| M | F | **M** | **F** | **M** | **M** | **F** | **M** | M | F | M | F |
| 1 | Early | 701 | 616 | 57.06 | 66.25 |  |  |  |  |  |  |  |  |
| 1 | Late | 613 | 699 | 55.72 | 64.73 |  |  |  |  |  |  |  |  |
| 2 | Early | 5117 | 4913 |  |  |  |  |  |  |  |  |  |  |
| 2 | Late | 3754 | 3356 |  |  |  |  |  |  |  |  |  |  |
| 3 | Early | 991 | 1228 |  |  |  |  |  |  |  |  |  |  |
| 3 | Late | 337 | 412 |  |  |  |  |  |  |  |  |  |  |
| 4 | Early | 3671 | 4404 |  |  |  |  |  |  |  |  |  |  |
| 4 | Late | 1717 | 1980 |  |  |  |  |  |  |  |  |  |  |
| 5 | Early | 3363 | 4451 |  |  |  |  |  |  |  |  |  |  |
| 5 | Late | 1244 | 1433 |  |  |  |  |  |  |  |  |  |  |

Table 4. Description of GAM- and Ecosystem-based Regions, and the sex-specific growth parameters estimated in the analysis. The Region column corresponds to regions depicted in Figure 8, with “early” period being observations before 2010. Parameter estimates are those used to plot fitted curves in Figure 9.

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