Hake Notes

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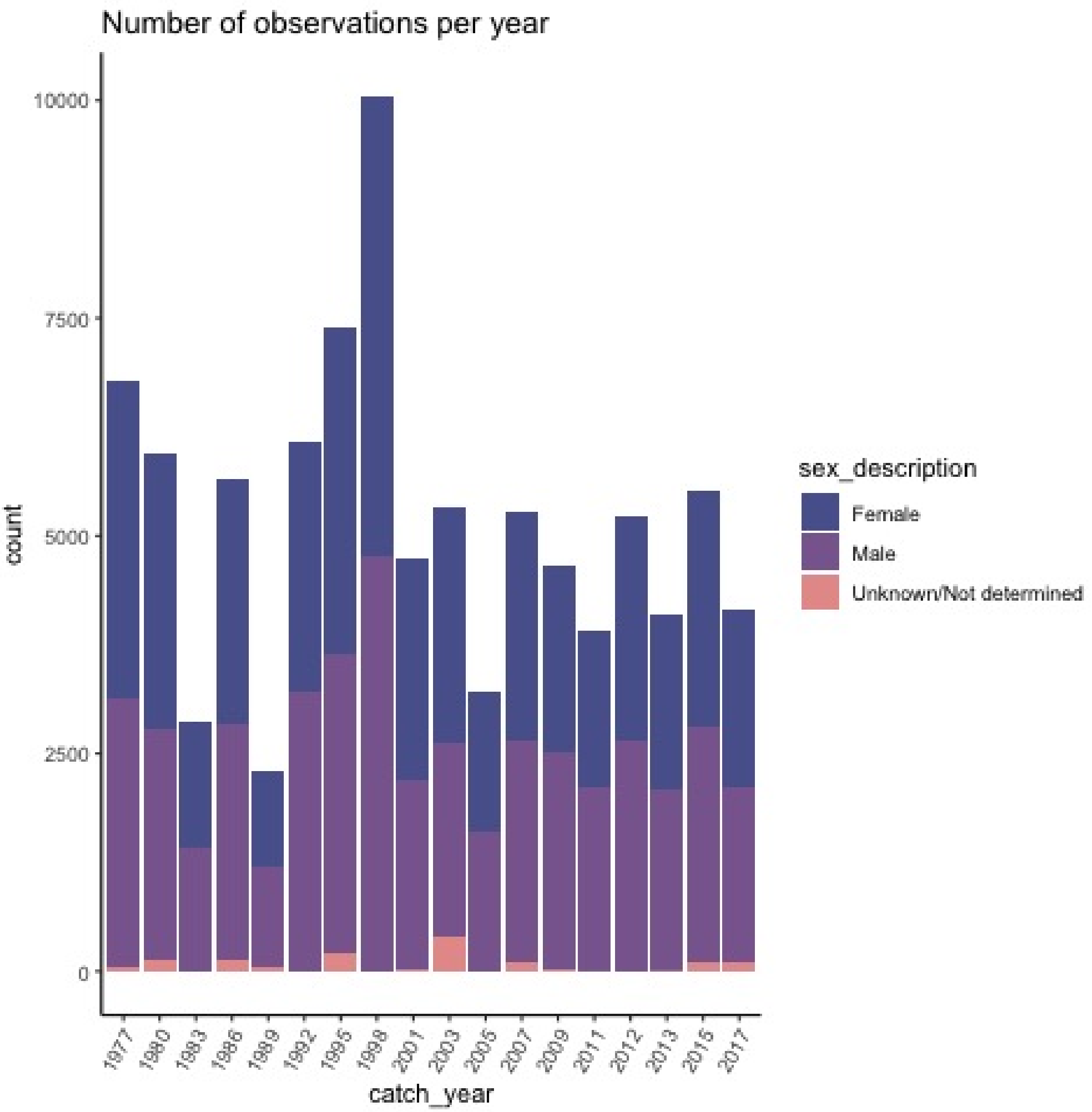
2022-07-04

Contents

June 27 - July 1, 2022

Received acoustic-trawl survey data through NOAA data warehouse - 103,245 observations. Data for 1980 - 2017 are included. I began by creating a new dataset, `hake_df` that included only Pacific Hake observations and relevant information (columns) - 93,186 observations. Date information from the `eq_date` column were used, however, observations with missing years were filled in using information from `hb_date` column. This constituted only observations from year 2017.



There are 46,816 female observations and 44,982 male observations. There seems to be a fairly equivalent number of males vs females.

Looking more closely at growth, particularly the relationship between length and weight, much of the unknown sex descriptions come from smaller sized fish which makes sense. Females and Males seem to follow very similar growth trends, as indicated by fitting separate growth models to each sex and estimated coefficients being fairly similar. Visually, there seems to be a greater abundance of females at those larger sizes.

Because of the similarity between males and females and because males and females are not modeled explicitly in the stock assessment, I went ahead and continued modeling the sexes aggregated together. I did this by first subsetting `hake_df` to observations that had complete length and weight information `fit_hake_df` - 52,382 observations. I log10-transformed the data (this was recommended over natural log transformation), and fit a linear model using `lm()`, a least squares method. The resulting model then became

$$log_{10}(W) = log_{10}(a) + b * log_{10}(L)$$

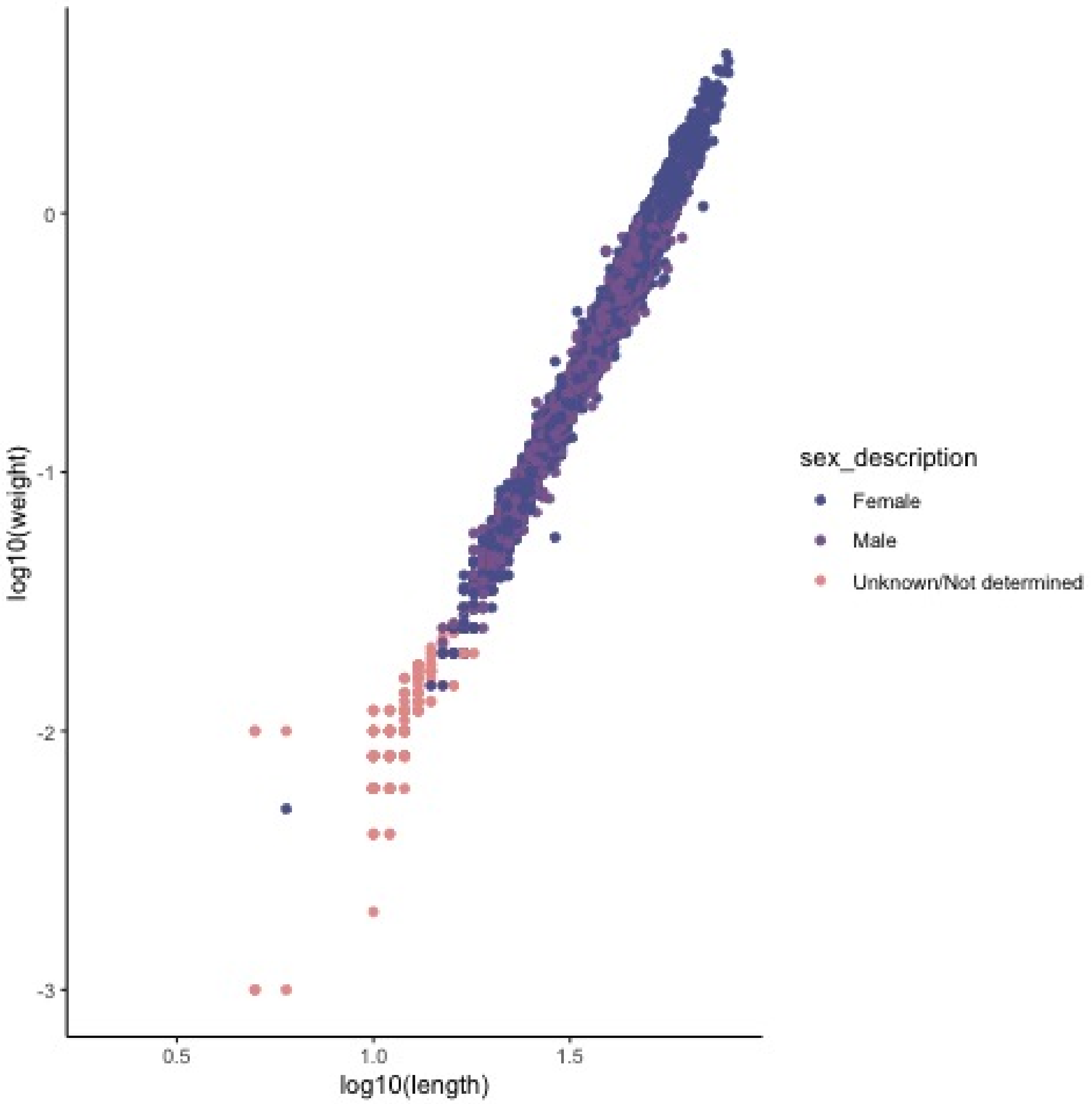


Figure 1: Log10-transformed length weight relationship

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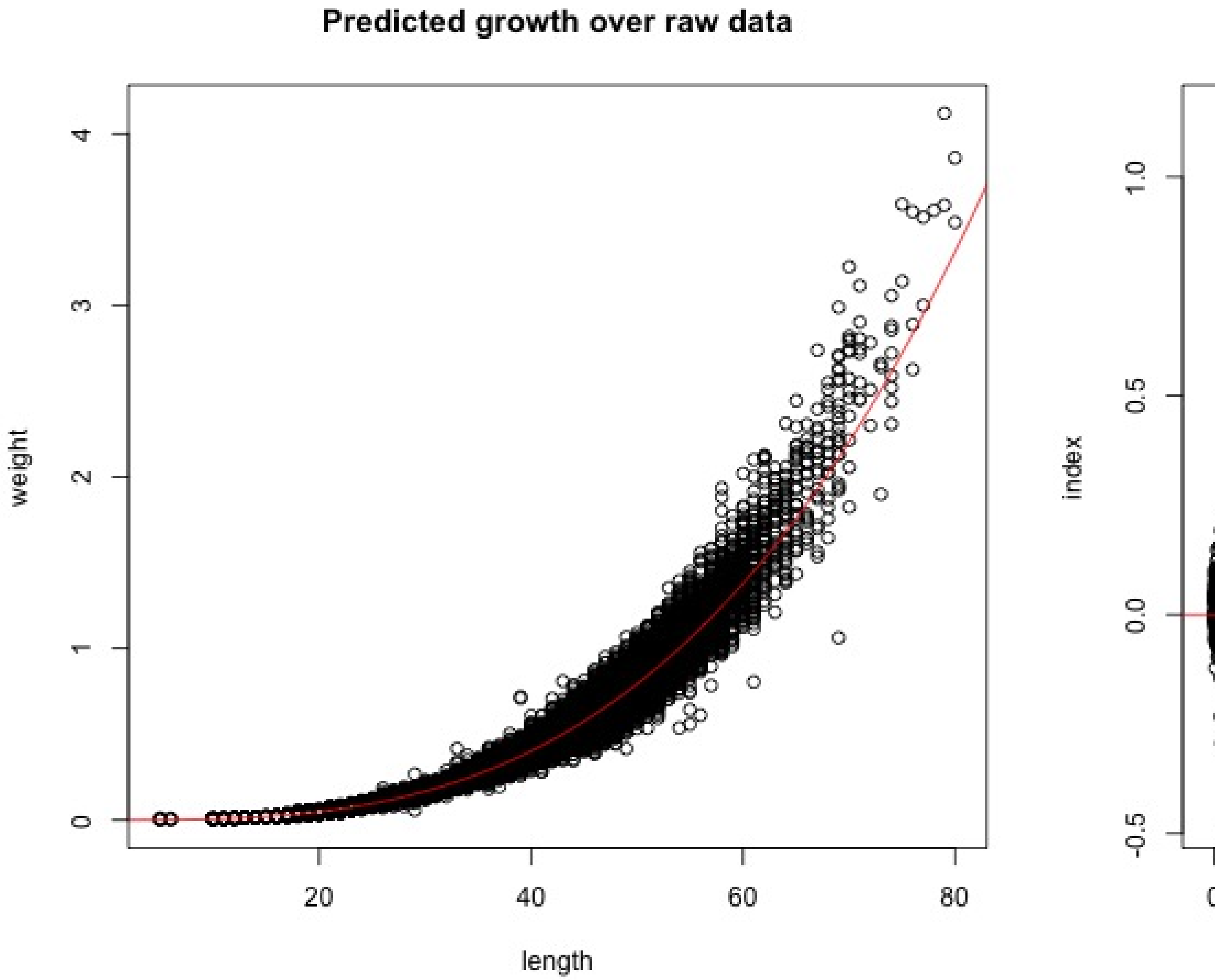


Above is the fitted model over the raw data and a plot of the residuals. The multuple R-squared value of the fit is 0.9819, which means that 98% of the variability can be explained by the model - which is great!

From now, I will be referring to residuals as growth anomalies (. . . makes more sense in my brain). These next few plots will be exploring patterns in growth anomalies as it relates to time, location, and age.

This first graph shows the variability in growth anomalies per year. Immediately, you notice that 1995, 2007, and 2017 have considerable variability in growth anomalies between individuals (i.e. there is a wide distribution of individuals who are both larger and smaller than normal). The distribution in 2007 is largely driven by 3 outliers, where those outliers are small (length) individuals that are much heavier (weight) than normal. I believe this may be due to measurement error. Years 1995 and 2017 are years adjacent to record warm years (marine heatwaves) which may have led to this variability in growth anomalies due to differential responses between fish (spatial or perhaps age?).

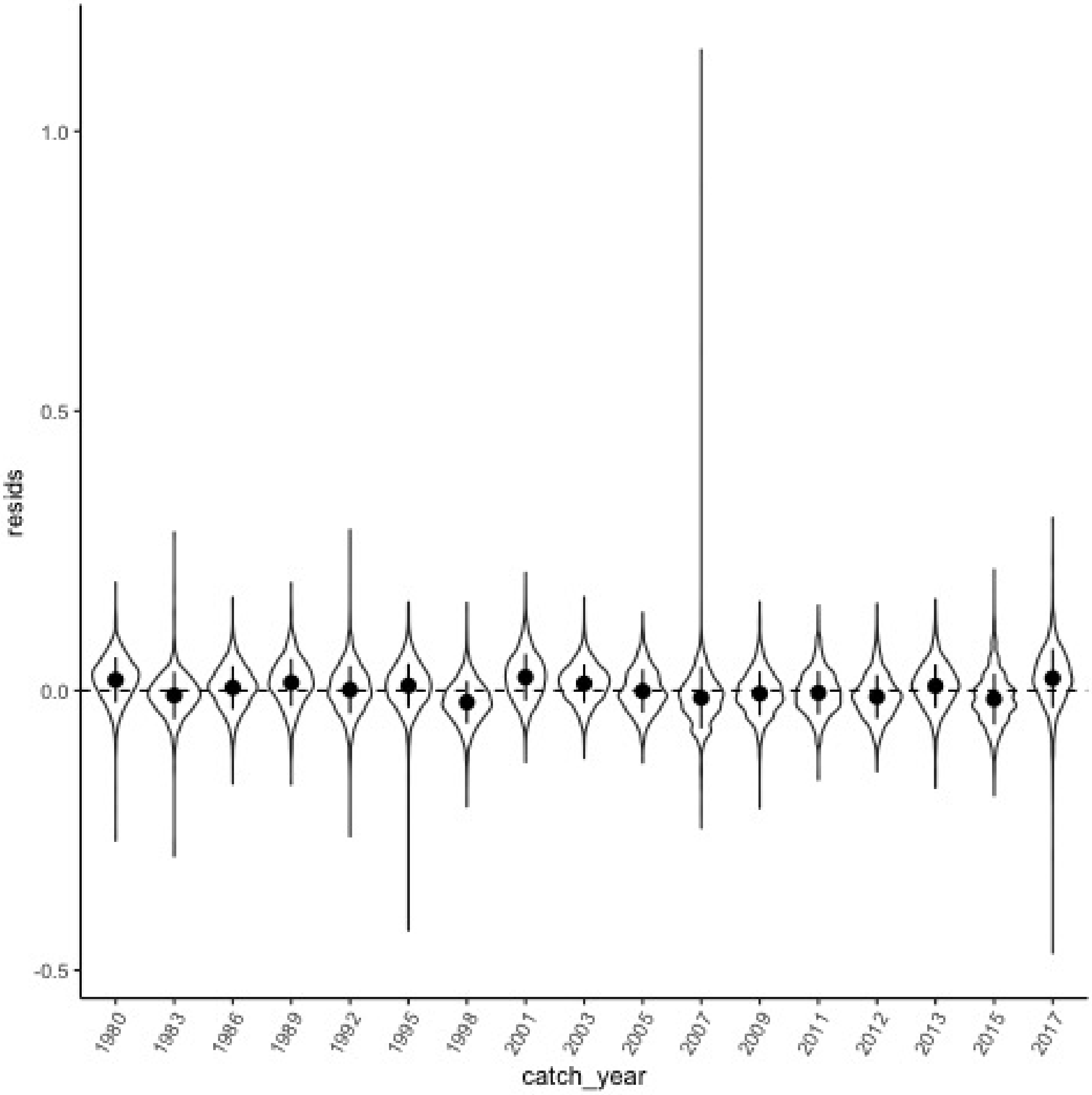


Figure 2: Summary of growth anomalies per year

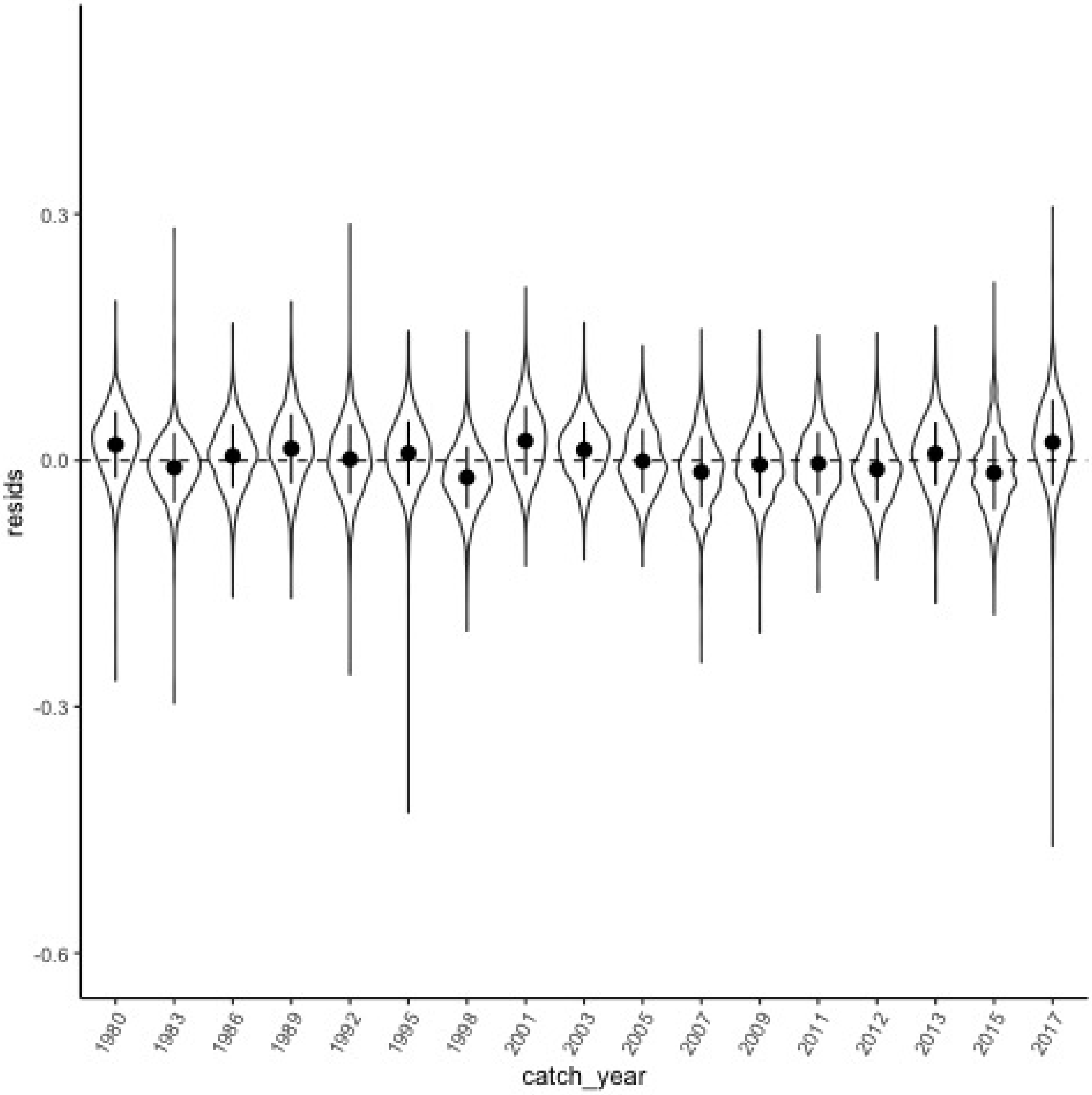


Figure 3: outlier removed

This plot removes the outliers from 2007. You can see that the 3 outliers really drive the distribution - how should we handle these outliers?

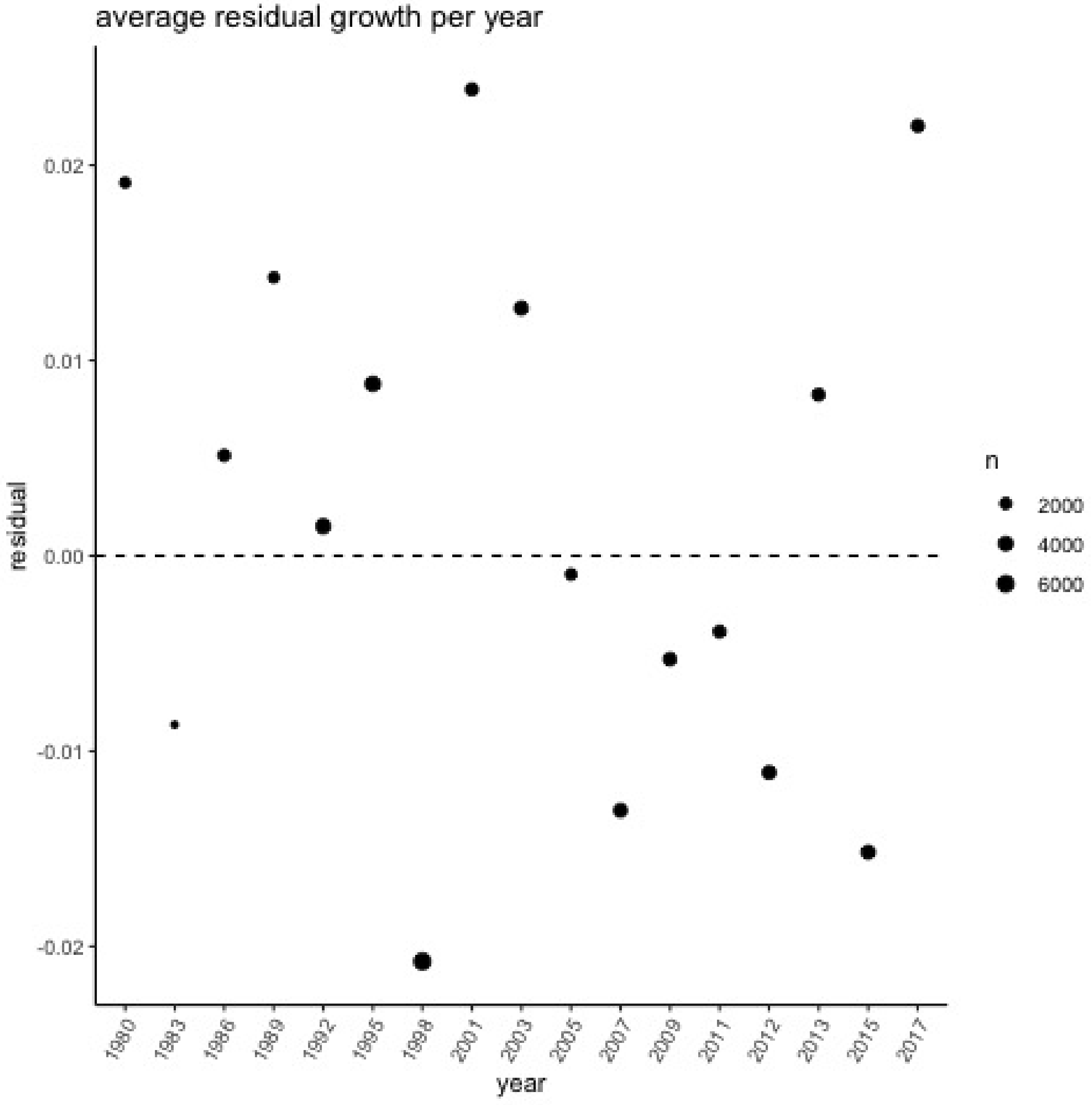


Figure 4: Avg growth anomalies per year

This plot is looking at the average growth anomalies per year without the spread of data. It looks like many of the years prior to 2003 were dominated by larger-than-avg individuals, except the year in which a marine heatwave occured. Following 2003, many of the years are dominated by smaller-than-avg individuals with the exception of 2013 and 2017.

This graph shows how growth anomalies vary along the west coast every year. Values close to 0 (i.e. observed value is close to predicted - no anomaly) are transparent for better visualization of + and - values. Moreover, those 3 outliers in 2007 are included in the graph, but not in the color scale limit, for improved visualization. You can see there is considerable year-to-year variation, where in 1998 and 2015 you see mostly smaller-than-avg fish all along the coast and aligns with the years with marine heatwaves. In some years, there seems to

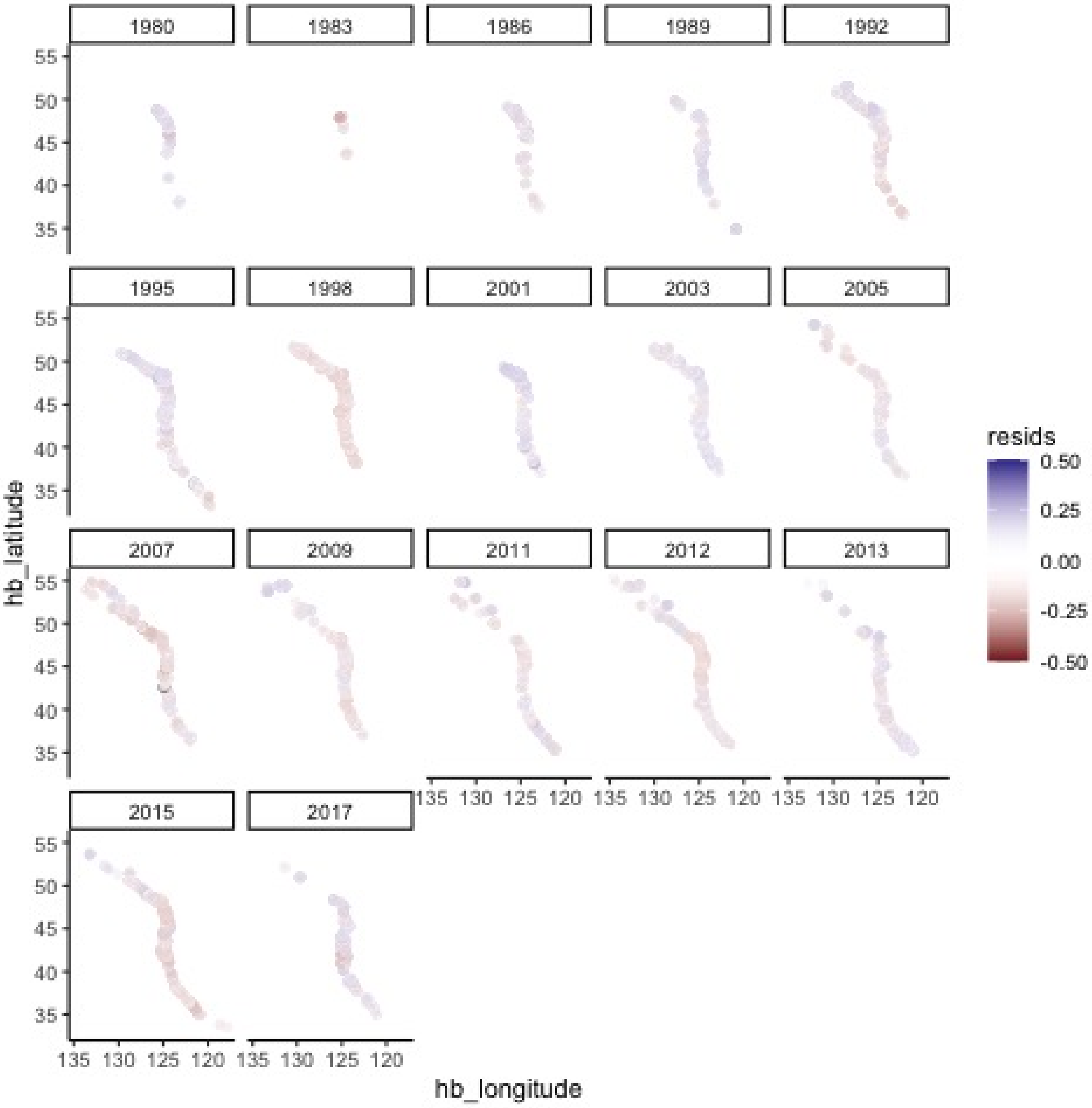


Figure 5: Spatial variation of growth anomalies by year

be a slight stratification, where the northern half of the coast shows larger or smaller-than-avg individuals and southern half vice versa. An issue with this graph is that you can't see individuals who do not exhibit a growth anomaly, which I think would be valuable to see if this occurs in a part of the coast.

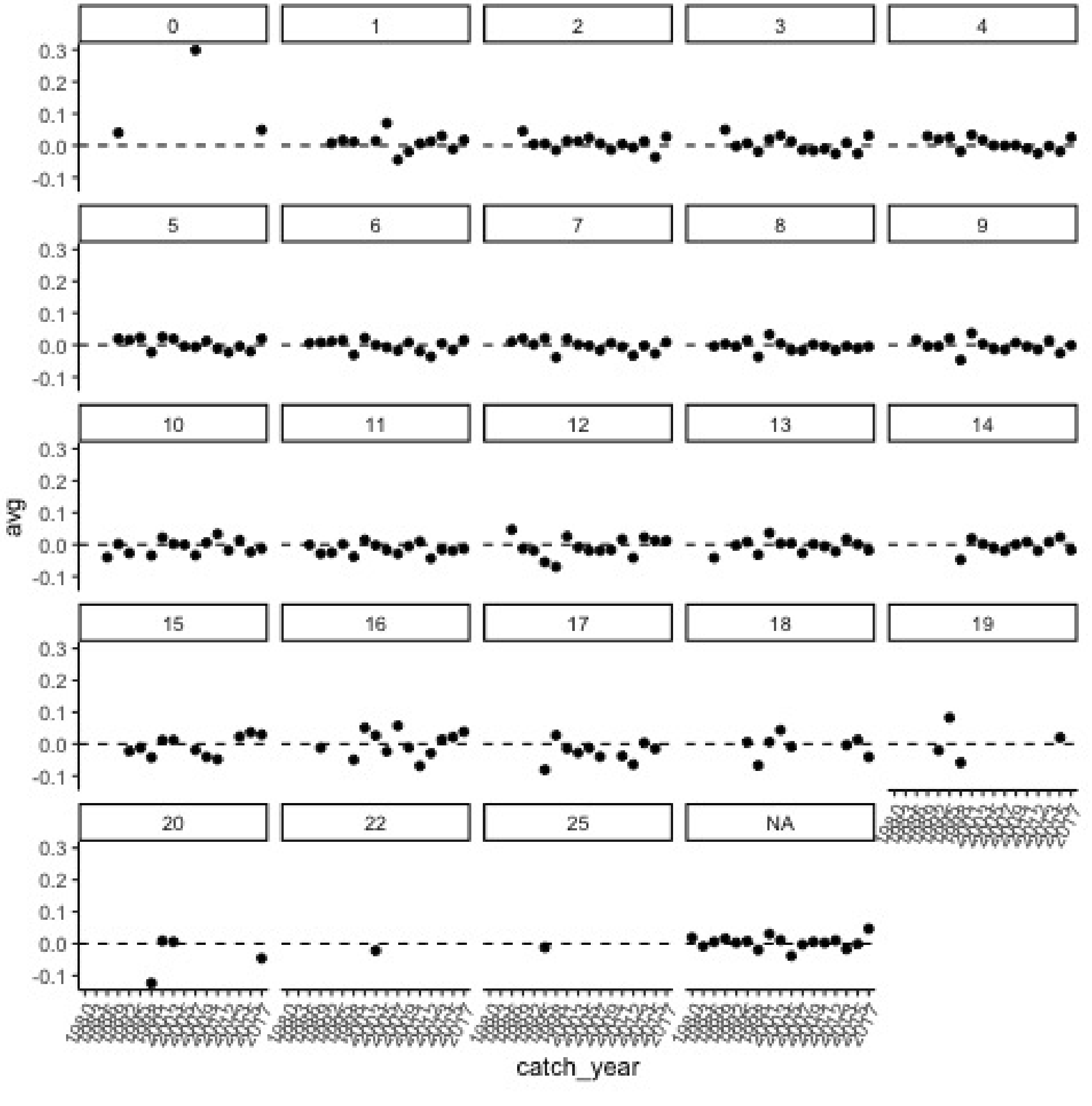


Figure 6: growth anomalies timeseries by age

A time series of average growth anomalies per age group. This essentially reveals how variable growth anomalies are per age - are some ages more vulnerable to variation in growth? are some age classes consistently larger or smaller than average? Either way, this plot is a little hard to decipher.

Summarizing the variability of growth anomalies per age even further, we can see that growth anomalies are most variable at age 0 - likely because there's fewer data and potentially greater measurement error - and that variability in growth anomalies increases slightly with age. However, there are fewer observations at those older age classes. I plan to create a plus group, by concatenating the age classes 15+ as done similarly in the stock assessment.

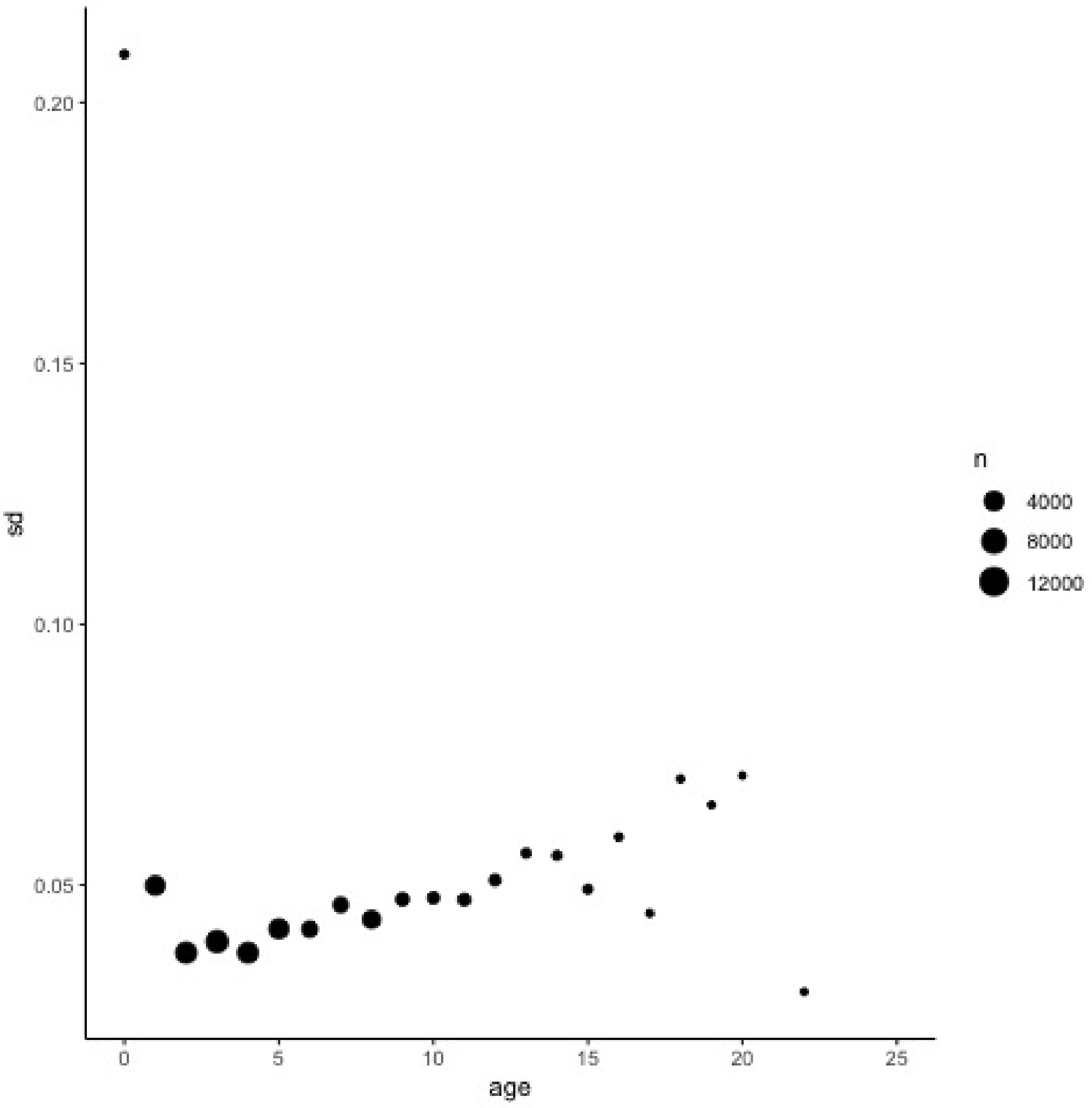


Figure 7: Variability of growth anomaly by age

July 4-8, 2022

Some next steps I plan to take this week is I will fit an age at length model to assign ages that don't have values. I will create a plus group age, grouping all ages 15 and greater. What sort of changes do we see when we make this assumption? I will explore finer temporal resolution to hopefully get an idea of some of the sampling/selectivity bias that might be happening. Another question was whether there was spatial variation in which sex dominates? All of this should then lead to some statistical modeling to determine relative importance of the patterns that I am seeing.

Okay, to start with estimating age using an length-at-age model, I first subsetted the `hake_df` dataframe so that there is only complete cases for age and length columns named `age_hake_df`. Then I added a new column `new_age` which were ages including plus group (ages 15+)

I first fit a Von Bertalanffy model to the whole data (all years combined), then fit a Von Bertalanffy model assuming "two regimes" where I fit the model to years 1980-2003 and 2004-2017, and finally I fit a Von Bertalanffy model to the plus group data. $size \sim L_\infty/(1 + exp(-K * (age - t_0)))$

I selected the regimes by visually determining years with the most similar average growth anomalies (1980-2003 had larger-than-avg individuals and 2004-2017 had smaller-than-avg).

There was negligible differences in fit and coefficients between the whole data scenario (RSS = 551852) and the plus group scenario (RSS = 551912). However, when the data was split into regimes the fit of the model improved as indicated by the Residual Sum Squares (RSS = 324002/200280).

Overall, the fits didn't look so great - there was a bit of underfitting over the age of 6. The graph below only shows fit for the whole data, however, there were

Because I created a plus group, I wanted to go back and look at some of the data visualizations I did last week to see if there were any big changes.

First, I looked at the variability in growth anomalies per age by plotting the residual standard deviation for each age. The size and color of the points indicate number of observations and whether the residuals are positive on average (i.e. larger-than average), respectively.

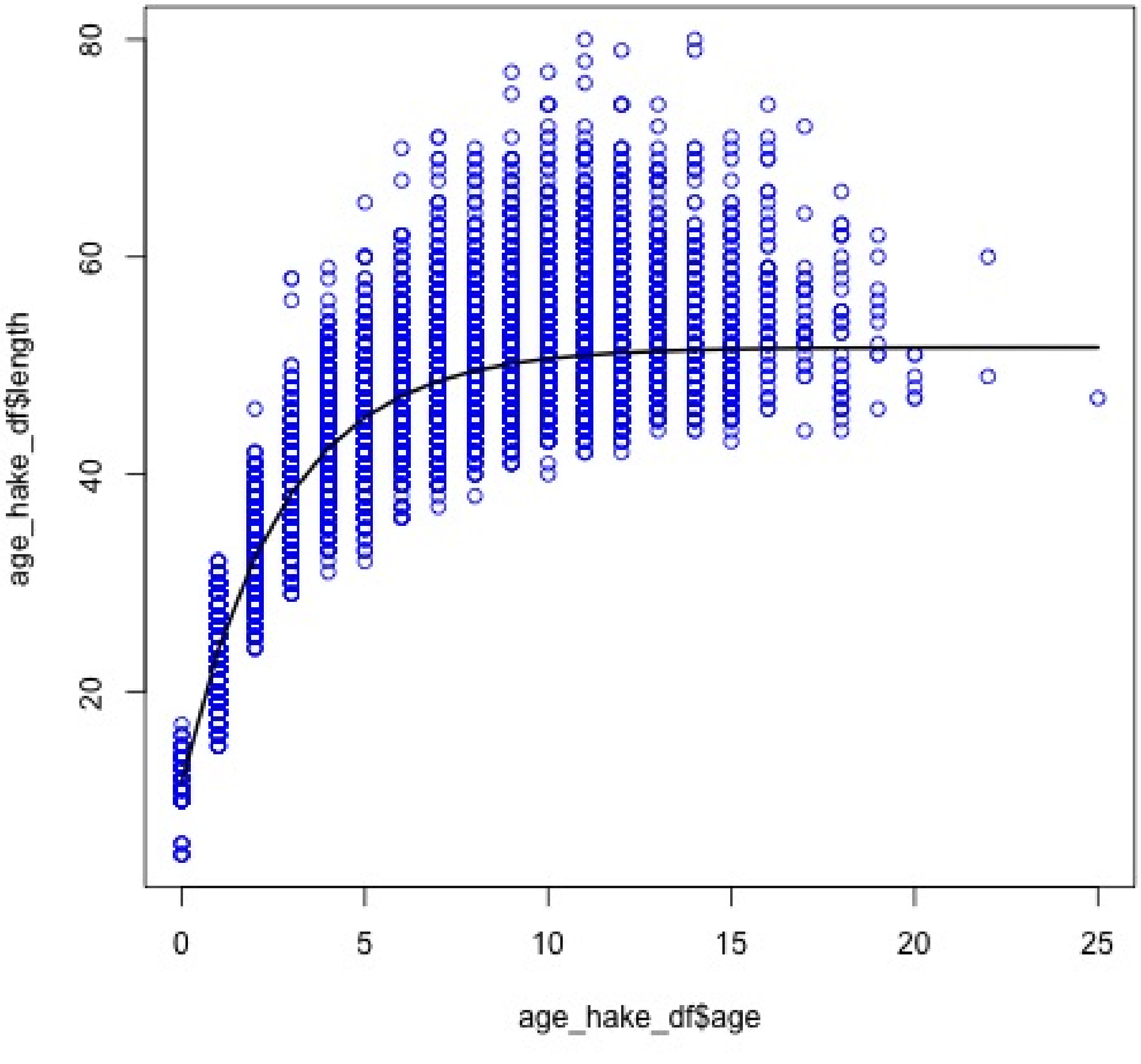
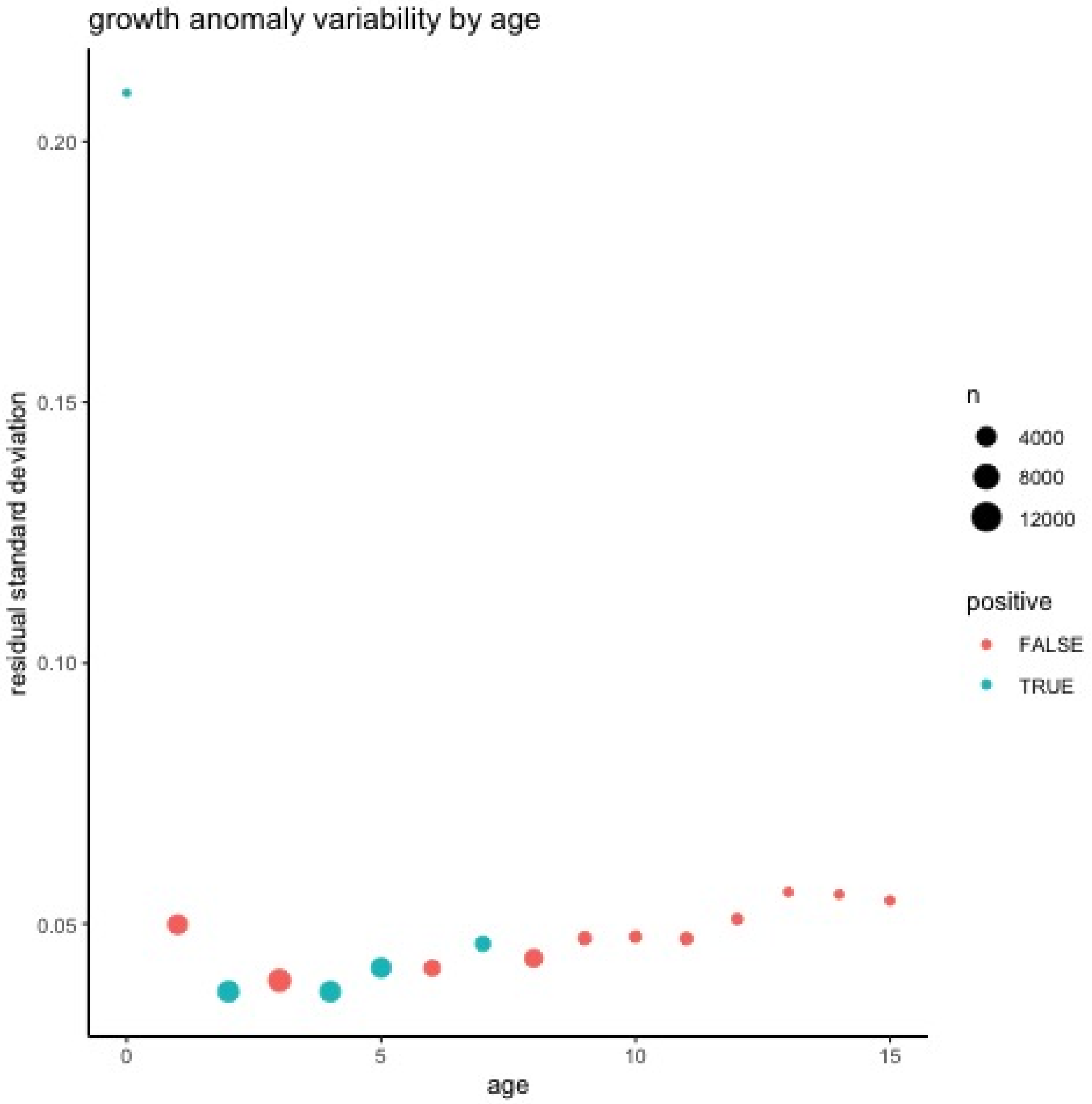
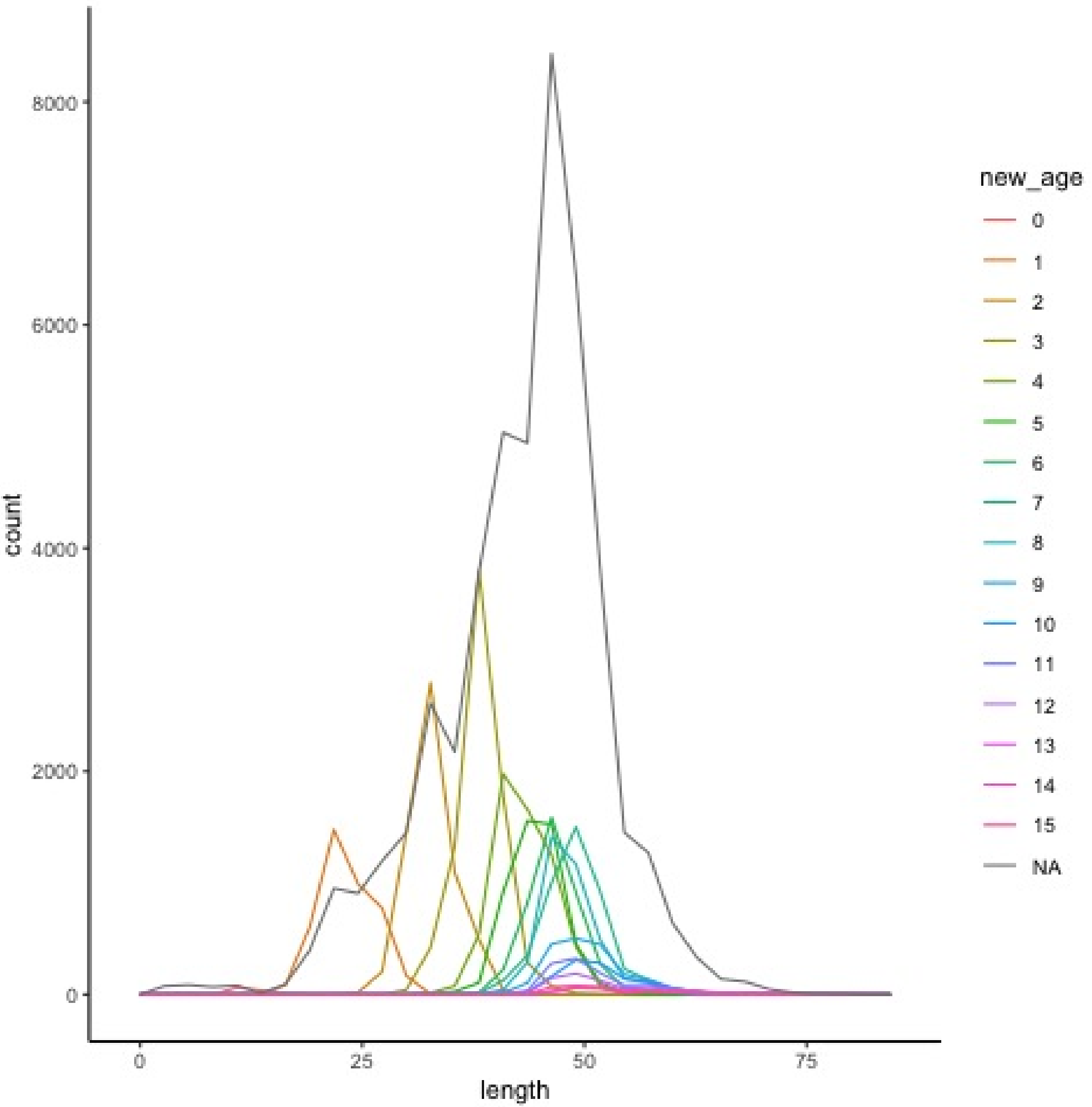


Figure 8: Growth curve to whole data



When estimating ages, it's worth making sure I understand what ages we are estimating. Below is a rough length frequency plot by age, where colors indicate age, and the grey line indicates observations that haven't been assigned an age. A lot of the observations with unassigned ages are larger individuals, and the VB models I have explored so far underestimate the ages of those larger indivudals. How should I proceed?



Looks like age 6+ are fairly similar lengths - increased potential for mis-assigning these ages?

In terms of the stock assessment, the 2006 assessment modeled growth 3 ways: time-varying K, density dependent growth, and cohort-specific K.

Notes from meeting with Kristin 7/7/22

- The weight/age/year data may not be considered confidential and could request to get that data.
- Interesting to look at spatial and temporal variation (check Maia Kapur's work).
- Potential big-picture questions
  - How can we leverage this information of growth anomalies? Are there cohort effects? Is there an effect on future spawning?
  - Are there bigger recruitment events in years with fatter fish?
  - Do fish that are fatter in the early lie stages, stay fatter throughout their life?
  - Ultimately, how can we develop a model that goes into the MSE?
- Next steps:

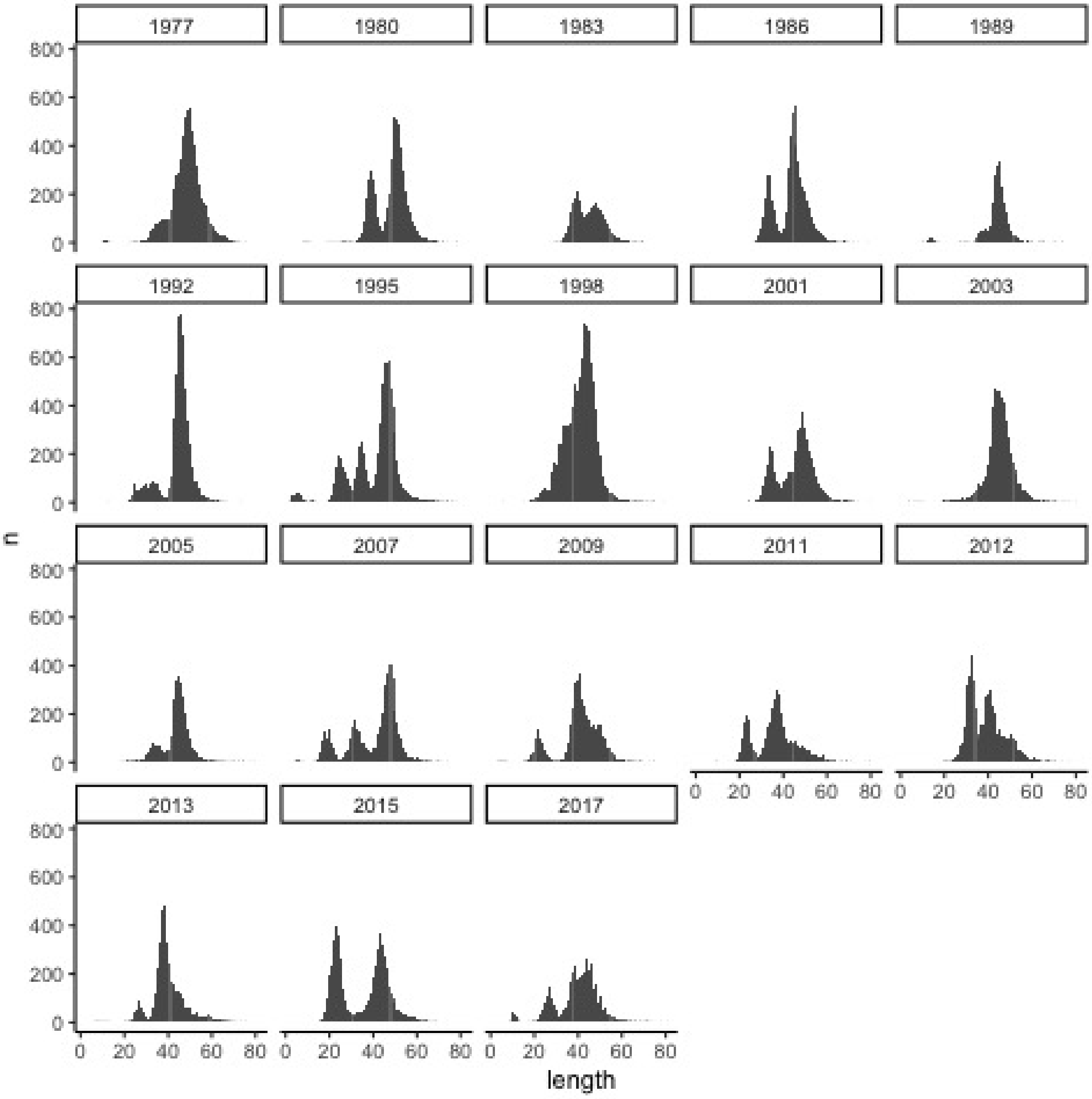
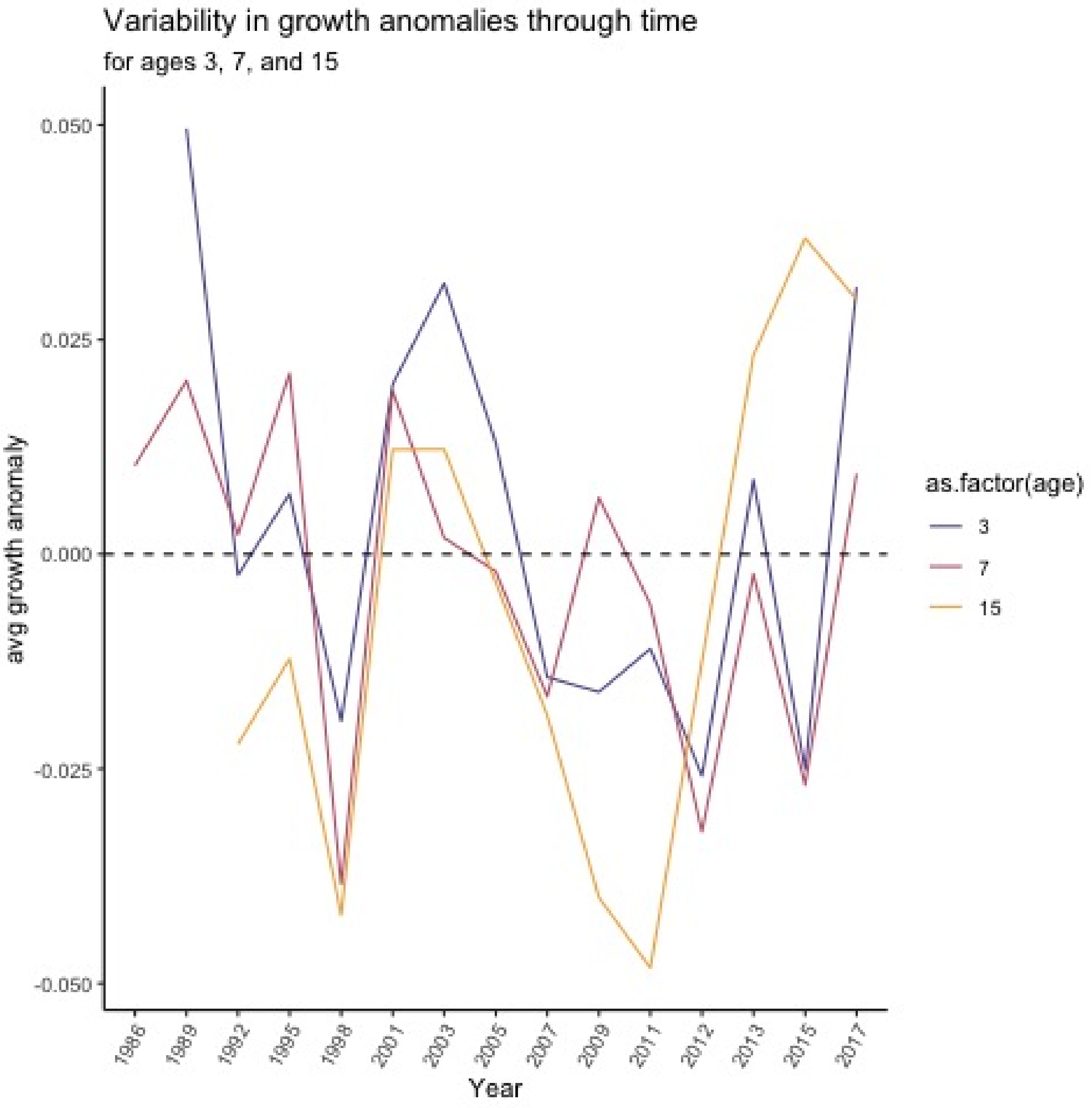


Figure 9: Length frequencies by year

- Still have to explore finer temporal resolution
- hierarchical or mixed growth model with time varying K

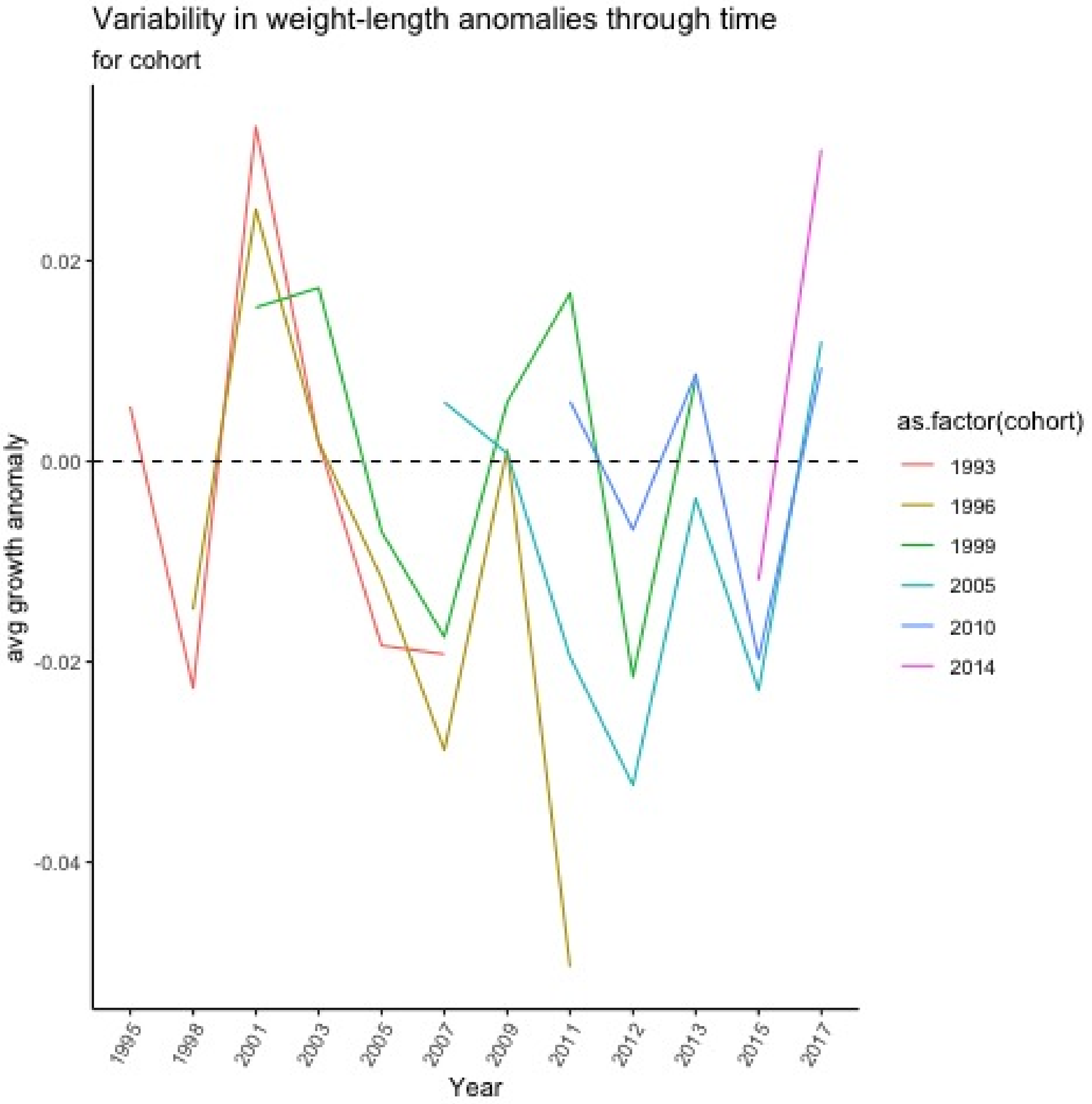
July 11-15, 2022

How do weight-length anomalies vary through time for a specific age?



It looks like fish condition for a younger ages vary much more stochastically compared to the plus group age that has much more low-frequency fluctuations. Potentially because they aren't growing quite as much at this age? Or lag effect with younger ages moving into this plus group?

And similarly, looking at how cohort condition varies through time



Doesn't look like there aren't too many patterns between cohorts.

- **Meeting with Kelli Johnson (7/14/22) on weight at age**
  - weighting process
    - summarizes the data and then use that to weight things
    - assumes all fish of the same age have the same weight
    - only use individuals with ages when working with age composition and weight at age
    - use individuals with length, weight, and age to groundtruth if needed
  - data_wtatage()
    - needs maturity ogive and catches to get mean weight at age. uses previous years to fill in missing age information
    - assumes every population process going through SS uses the same weight at age (between different data sources - fishery vs survey vs etc)
    - sampling date as potential covariates (do we need to take into account sampling month when we do weighting?)

        - could model season (season just means month) but the caveat is that we need to fill in everything, and so that's just more estimating ages
        - if the estimated ages look the same regardless if we add biological realism then who cares
        - female only modeled
        - ignoring this dilutes the potential that surveys/data sources are sampling different fish
        - may need some way to fill in missing information better based on the results that we (kristin and i) find
            - what if there's a regime shift but we don't account for that
            - are there environmental covariates that may drive changes in weight at age?
        - SS there's flexibility in how you want to fill in these values
        - factors influencing weight at age
            - sampling bias
            - cohort effects
            - environmental effects
        - check how Pollock assessment fills in missing information
        - Sablefish also has a lot of data to test on
        - visualize weight at age over the raw data to see if there are strong cohorts coming through
        - Line 157 in github code - beginning of where they fill in missing values

- **Meeting with Kristin**
    - random effects
        - year
        - cohort
        - to establish cohort, we can create a cohort ID that is their birth year (cohort ID = current year - age) - We could also look at how growth anomalies relate to the size of the population or cohort to get into some density dependence effects
    - 3 potential ways to model weight at age
        - random effect just on age
        - gam (does brms have gams)
        - boosted regression trees
            - Doesn't give insight into mechanism, so might be difficult to translate into something for MSE
    - For the growth anomaly variability line graph, we could also look at
        - ages 1 and 2
        - immature vs mature fish
        - To think about: age 3 fish have fairly variable growth anomalies and they are also the biggest contributor to recruitment
            - how does this variability affect population dynamics
    - Note: big cohorts happened in 1999 and 2010

I tested out different GAMs using `gam()`, as well as running it in `brms`.

1. Simple GAM with no random effects

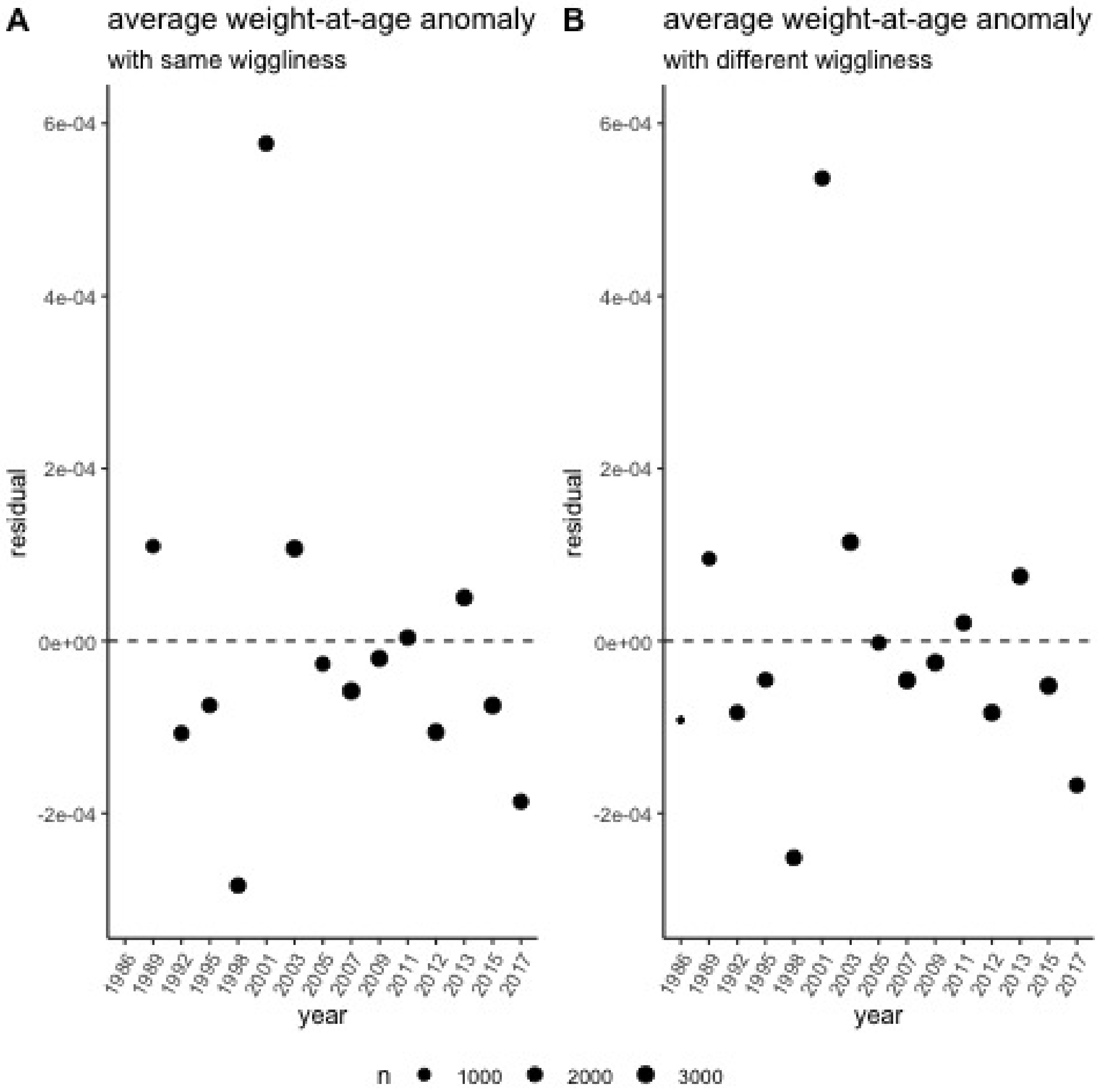
```r
gam_out <- gam(weight ~ s(new_age), data = hake_weight_age_df, method = "REML")
```

2. GAM with group-level smoothers with different wiggliness for year

```r
gamm_out = gam(weight ~ s(new_age, bs="tp") +
      s(new_age, by = catch_year, m = 1, bs="tp") +
      s(catch_year, bs="re"),
      data = hake_weight_age_df, method="REML")
```

3. GAM with group-level smoothers with same wiggliness for year

```r
gamm_GS_out = gam(weight ~ s(new_age, m = 2) +
                 s(new_age, catch_year, bs="fs", m = 2),
               data = hake_weight_age_df, method="REML")
```

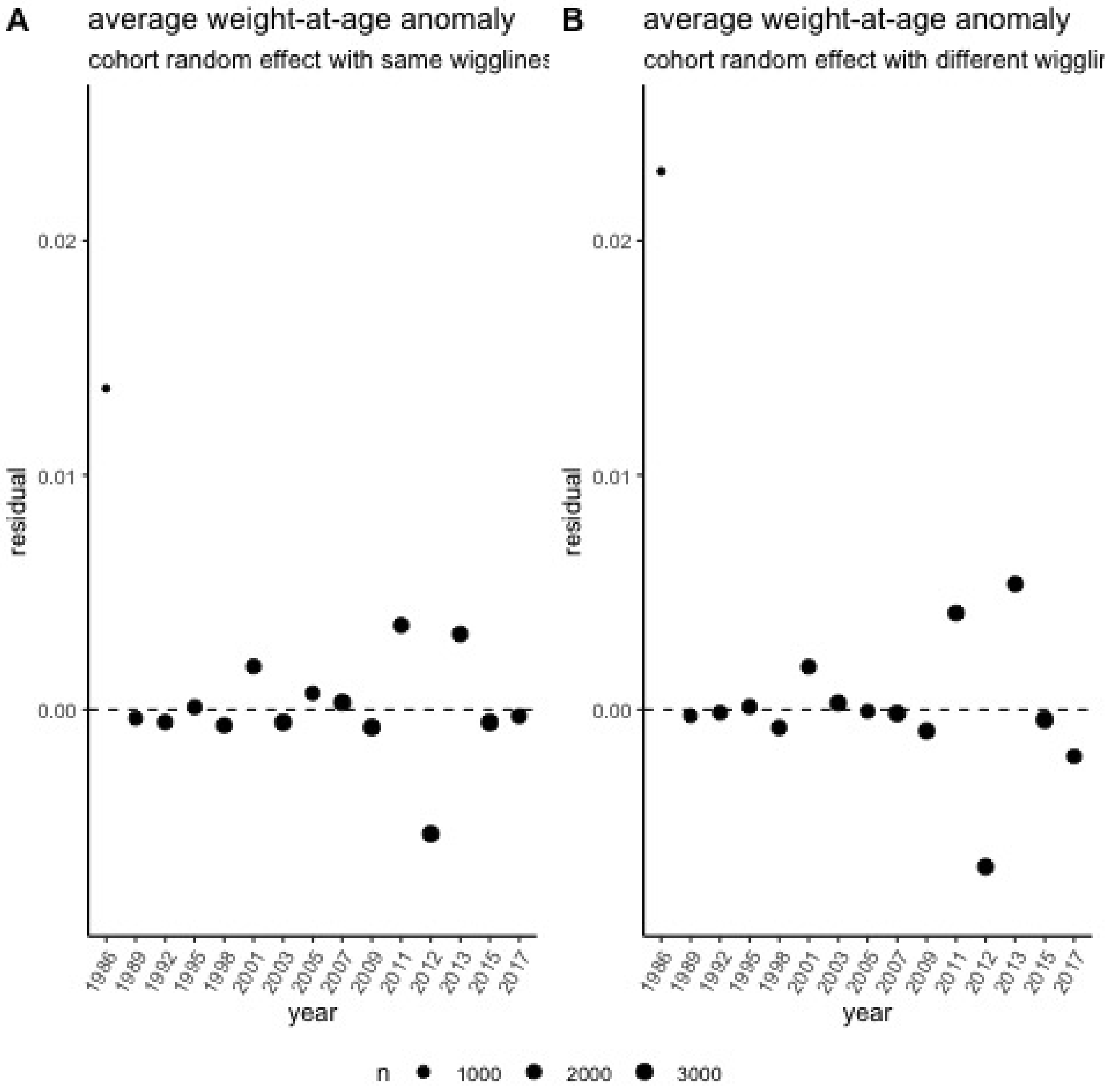


4. GAM with group-level smoothers with different wiggliness for cohort

```
gamm_cohort_out = gam(weight ~ s(new_age, bs="tp") +
                        s(new_age, by = cohort, m = 1, bs="tp") +
                        s(cohort, bs="re"),
                      data = hake_weight_age_df, method="REML")
```

5. GAM with group-level smoothers with same wiggliness for cohort

```
gamm_GS_cohort_out = gam(weight ~ s(new_age, m = 2) +
                    s(new_age, cohort, bs="fs", m = 2),
                  data = hake_weight_age_df, method="REML")
```



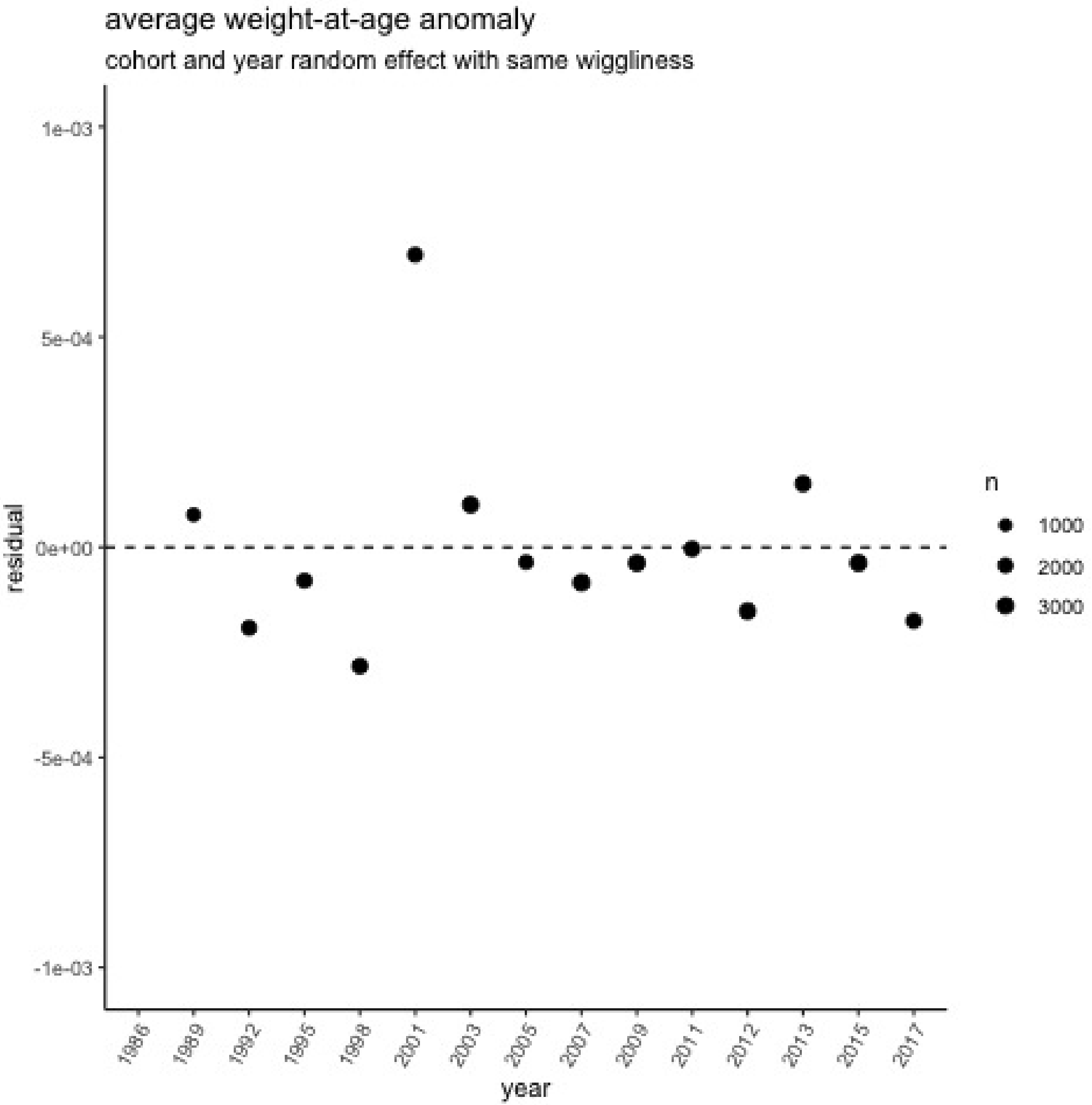
July 18-22, 2022

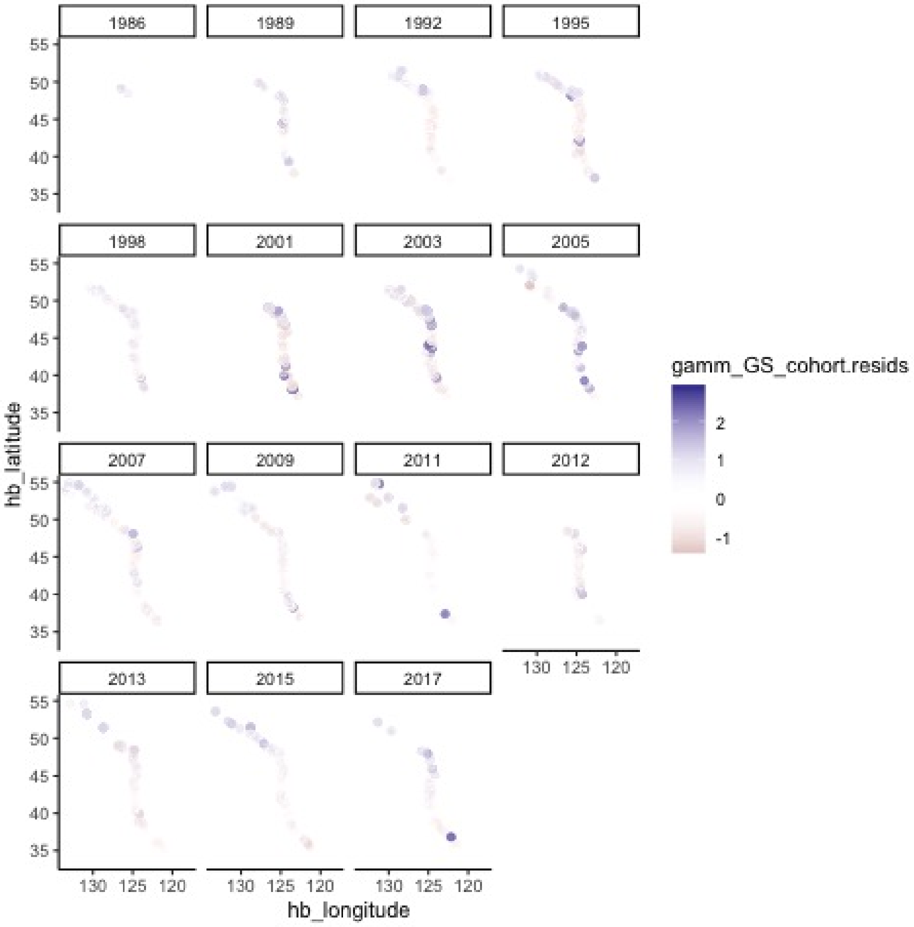
Of all 5 models, `gamm_GS_cohort_out` had the smallest AIC value.

- Notes on weight-length and weight-at-age and how they may relate
    - weight-length relationships are indicative of "body condition"
    - weight-at-age is a rate, so potentially indicative of growth rate

6. GAM with group-level smoothers with same wiggliness for cohort and year

```
gamm_GS_year_cohort_out = gam(weight ~ s(new_age, m = 2) +
                               s(new_age, cohort, bs="fs", m = 2) +
                               s(new_age, catch_year, bs="fs", m = 2) ,
                             data = hake_weight_age_df, method="REML")
```


average weight-at-age anomaly
cohort and year random effect with same wiggliness
residual
1e-03
5e-04
0e+00
-5e-04
-1e-03
year
1986
1989
1992
1995
1998
2001
2003
2006
2007
2009
2011
2012
2013
2015
2017
n
1000
2000
3000



Looking at how weight-at-age anomalies vary spatially by year, there seems to be a lot more within year, spatial variation compared to between years. This is in stark contrast from visualising the length-weight relationship. This plot only shows for the gam model with cohort RE and same wiggliness (model 5). However, there were no visual differences between the other models that I tried (model 3 and 6).

Okay, I need a recap:

- weight-length relationship
  - greater year-to-year spatial variation
  - plus group has lower freq variability through time vs younger ages are much more stochastic
  - No clear pattern between cohorts when looking at weight-length variability through time
- weight-at-age
  - greater within-year spatial variation
  - Different temporal trends in average growth anomaly depending on model used

Meeting with Kristin

- gams
  - don't put smoothers on random effect
- year-to-year effects are better explained because the residuals are smaller
- write down hypothesis about how weight-at-age should vary with cohorts or years
  - different curve for each cohort
- LOOIC instead of AIC (look at Michael Malick papers 2020)
- Think about what I want to get out of the internship and make sure we're accomplishing that

July 25-29, 2022

Potential questions of interest
- Explore spatio-temporal patterns in growth of Pacific Hake
- Identify potential covariates of growth trends and develop an environmental index
- Quantify the performance of incorporating an environmental index on growth
- Separately, test importance/sensitivity of SS of filling in missing weight-at-age information assuming average vs environmentally driven weight-at-age
- Incorporate into the MSE?

Goals for the rest of the summer
- Solidify motivation and guiding questions
- Identify promising methods/approaches
- Begin writing

This week I did more work on the gam modeling and now have a better grasp on what I am modeling. Last week, the models I was fitting were gam models with "random wiggliness" where each cohort and year had their own wiggliness/spline action. However, we are more interested in random effects where there is just a shift in the position of the curve (intercept?), but the shape remains the same. With that in mind, I realized we could still use the smoothing function (because smoothing process also involves shrinkage and has a direct link to the shrinkage involved in random effects) and specify `bs = 're'`.

I just tested a Bayesian GAMM with year and year+cohort random effects.

1. Bayesian GAMM with only year RE

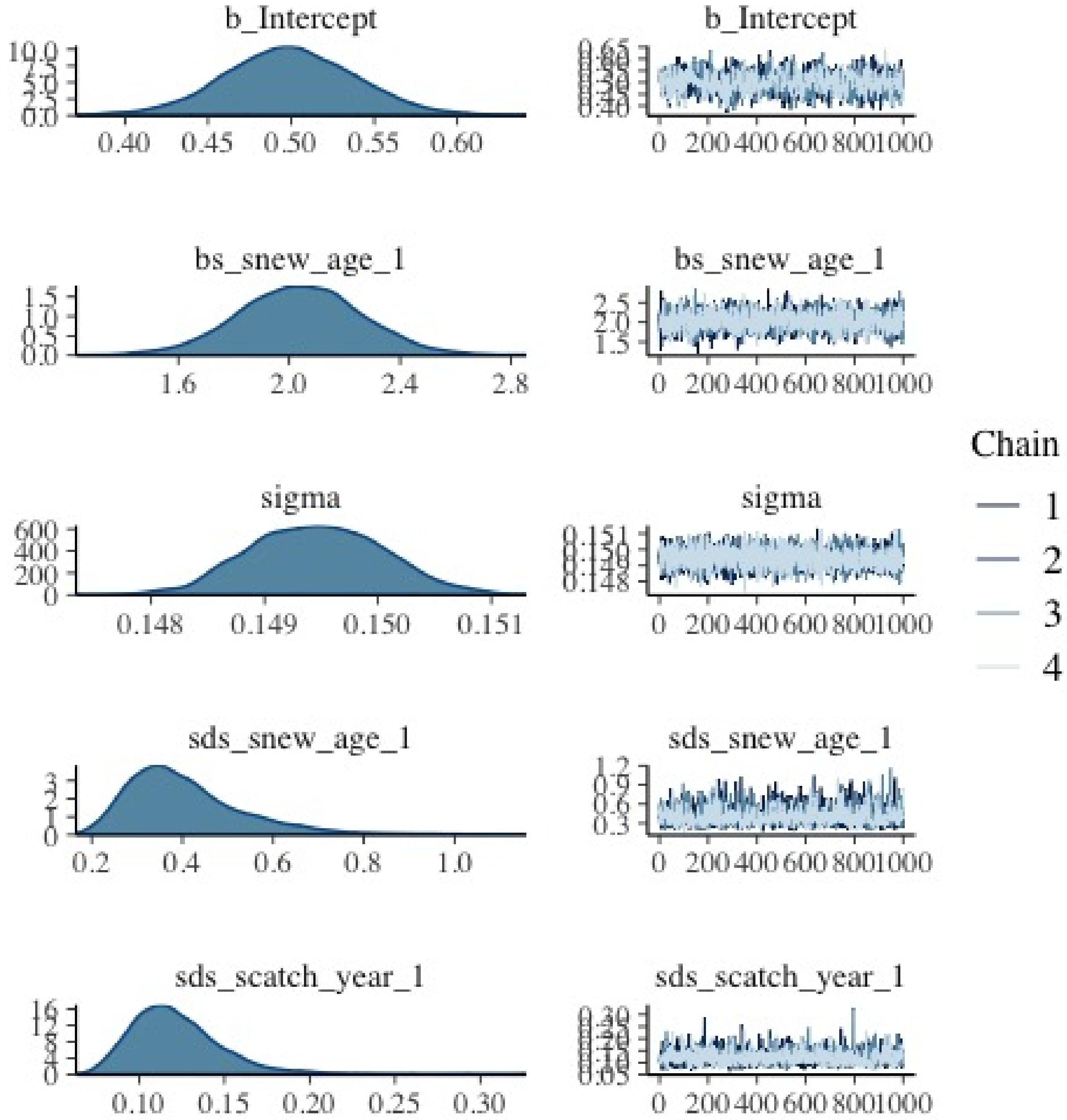
```
gamm_year_brm_out = brm(bf(weight ~ s(new_age) + s(catch_year, bs="re")),
                    data = hake_weight_age_df, family = gaussian(), cores = 4,
                    iter = 2000, warmup = 1000, chains = 4)
```

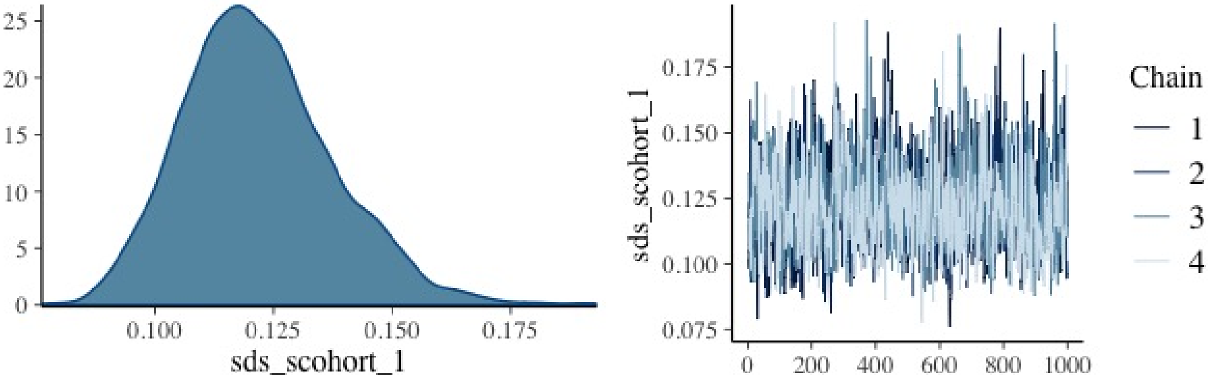
2. Bayesian GAMM with year and cohort RE

```
gamm_year_cohort_out = brm(bf(weight ~ s(new_age) + s(catch_year, bs="re")
                              + s(cohort, bs="re")), data = hake_weight_age_df, family = gaussian(),
                           cores = 4, iter = 2000, warmup = 1000, chains = 4)
```

Model comparisons: elpd_diff se_diff gamm_year_cohort_out 0.0 0.0 gamm_year_brm_out -1632.4 110.9

Because the model with year + cohort RE was a better fit to the data, I continue on only looking at that model

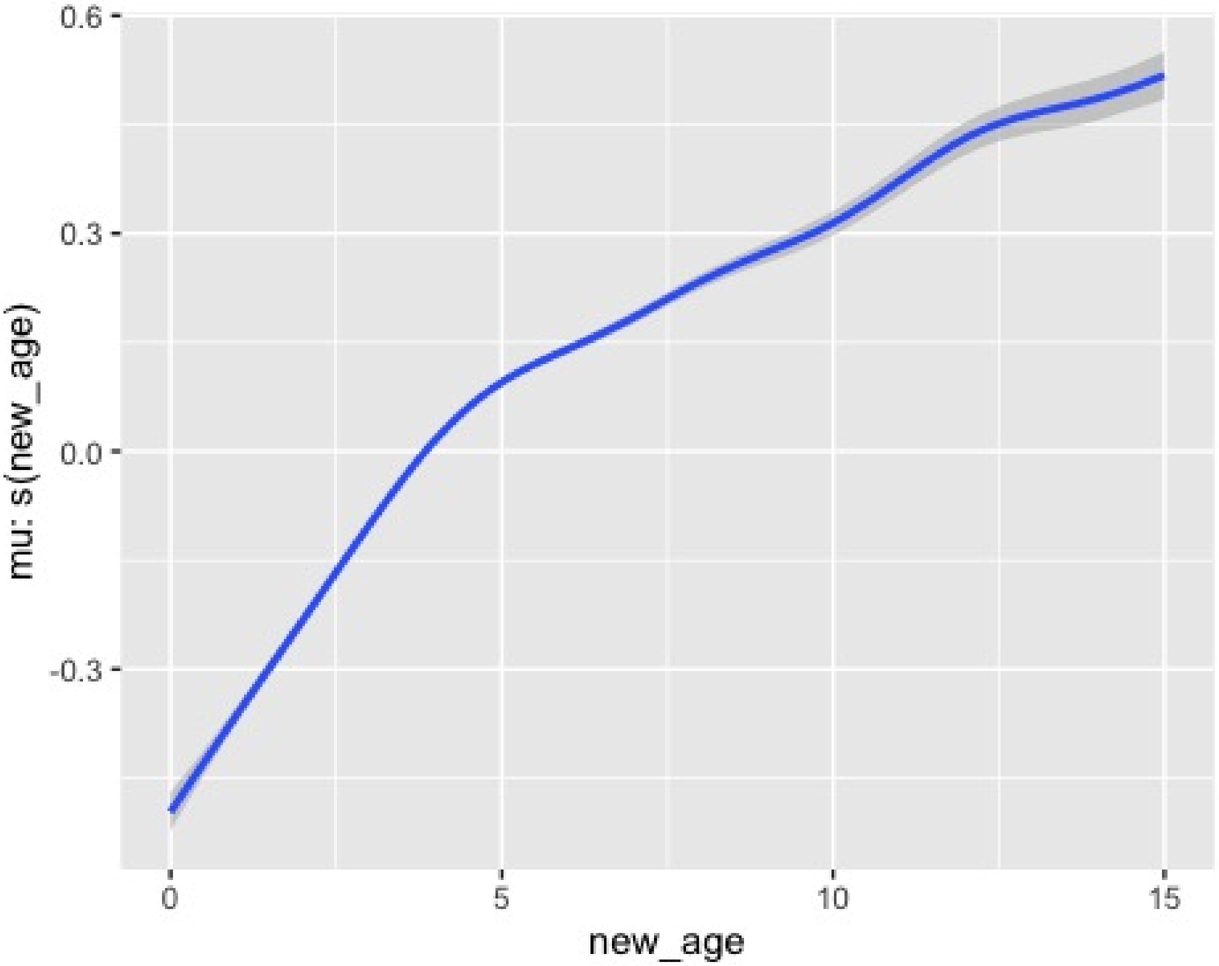

b_Intercept
10.0
7.5
5.0
2.5
0.0
0.40
0.45
0.50
0.55
0.60
b_Intercept
0.65
0.40
0
200
400
600
800
1000
bs_snew_age_1
1.5
1.0
0.5
0.0
1.6
2.0
2.4
2.8
bs_snew_age_1
2.5
2.0
1.5
Chain
1
2
3
4
sigma
600
400
200
0
0.148
0.149
0.150
0.151
sigma
0.151
0.150
0.149
0.148
sds_snew_age_1
3
2
1
0
0.2
0.4
0.6
0.8
1.0
sds_snew_age_1
1.2
0.9
0.6
0.3
sds_scatch_year_1
16
12
8
4
0
0.10
0.15
0.20
0.25
0.30
sds_scatch_year_1
0.30
0.05

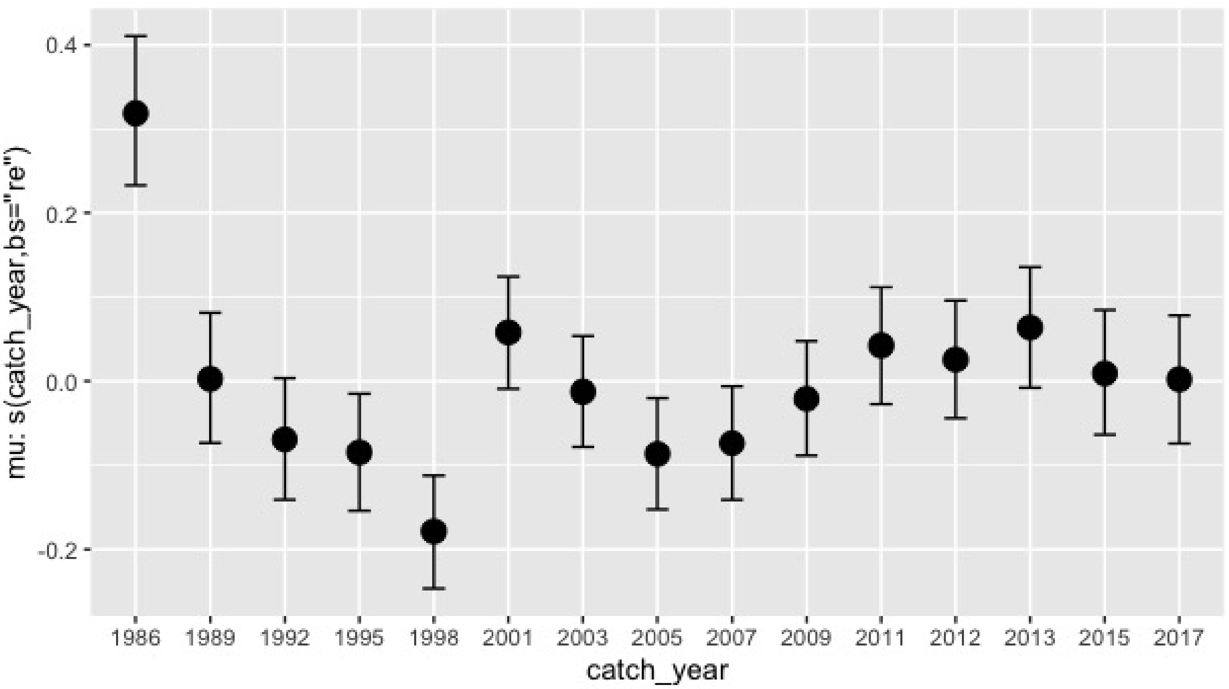

25
20
15
10
5
0
0.100
0.125
0.150
0.175
sds_scohort_1
sds_scohort_1
0.175
0.150
0.125
0.100
0.075
0
200
400
600
800
1000
Chain
1
2
3
4

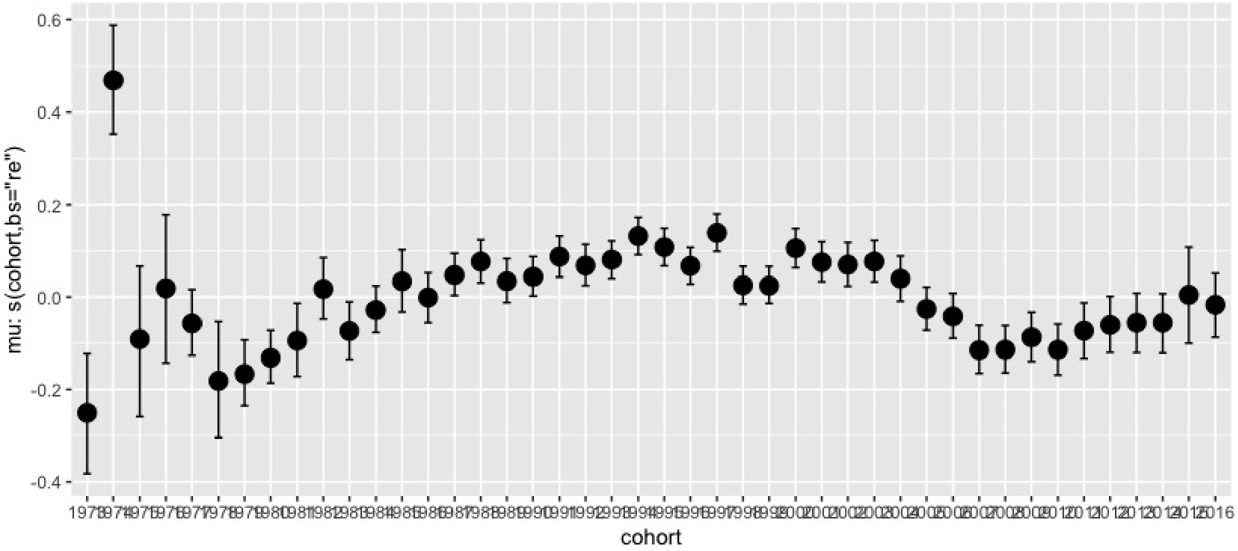
Density and traceplots look good - got the hairy caterpillars

However, the posterior predictive check doesn't look quite as good. This plot shows the observed data (in dark blue) and simulations from the joint posterior predictive distributions (in light blue). The replicated data should align with the observed data, unless there is model misfit or by chance. I used a gaussian distribution, however there is a bit of a right skew and potentially a lognormal or gamma distribution might be a better fit. I really have no clue what might be causing the multi-modes though… thoughts?

Either way, the next few plots will be summaries of the coefficients.







I am still trying to figure out how to graph these myself so that I can customize the graphs, but for now these will do..

Very clear year and cohort effects, some with credible intervals not passing over 0. Does that mean something like how it means in confidence intervals?

Questions

- How to best explore "year" and "cohort" effects - is just specifying random effects okay?
    - are these effects important and how important are they relative to each other?
        - have a model for each (no RE, just cohort, just year, both)
        - look at sd for year vs cohort. which has more variability
- where can I get recruitment and biomass information?

Questions for presentation in hake meeting

- potential environmental covariates to explore linked to growth? What is available?

- spatio-temporal methods?
    - sdm-TMB

    - gam with smoothers on lat,long

- thoughts on length-weight vs weight at age?

- Other assessments that use environmental indicators/indices that I can gain inspiration from?
- proposed research questions

Meeting with Kristin]

- what makes weight at age different from recruitment? there is no real way to put an environmental driver into stock assessment since it is empirical
    - rather, explore how incorporating an environmental driver affects the matrix of weight at age that does go into the assessment
    - MSE: historical period using same empirical weight at age as estimation model, future assumes average weight at age (not a good assumption)
- Fix assumed distribution in brms (lognormal/gamma)
- does spatial matter? If not, then we can lump data together with fishery data and get a longer time series
    - dig into smaller time-scale
- Next steps
    - model comparison
        - add smoother on lat,long (start simple model with just weight at age no RE)
    - identifying potential covariates
        - temperature, upwelling, decadal?
- recruitment and biomass information
    - pacific hake mse github - assessment repository
    - include as a potential driver

Aug 1-5, 2022

Notes from presentation

- Kelli: cohort effect of ageing error
    - strong cohorts have more ageing error
        - can lead to unequal smoothing
        - smoother would be smoothing out ageing error?
        - in stock synthesis, treat strong cohorts differently
    - maybe add a cohort effect for large cohorts
    - Kiva doesn't think it's that important (error in variables)
    - Even if I don't include it in the model immediately, it could be a way to explain some of the results
- For gamm with year and cohort random effect, there was agreement on the presence of autocorrelation in the cohort random effect
    - perhaps above average weight at age carrying through
- In terms of temporal trends, previous surveys were a different temporal window. If we could show that there are no differences in short timescale, then that's also good to know

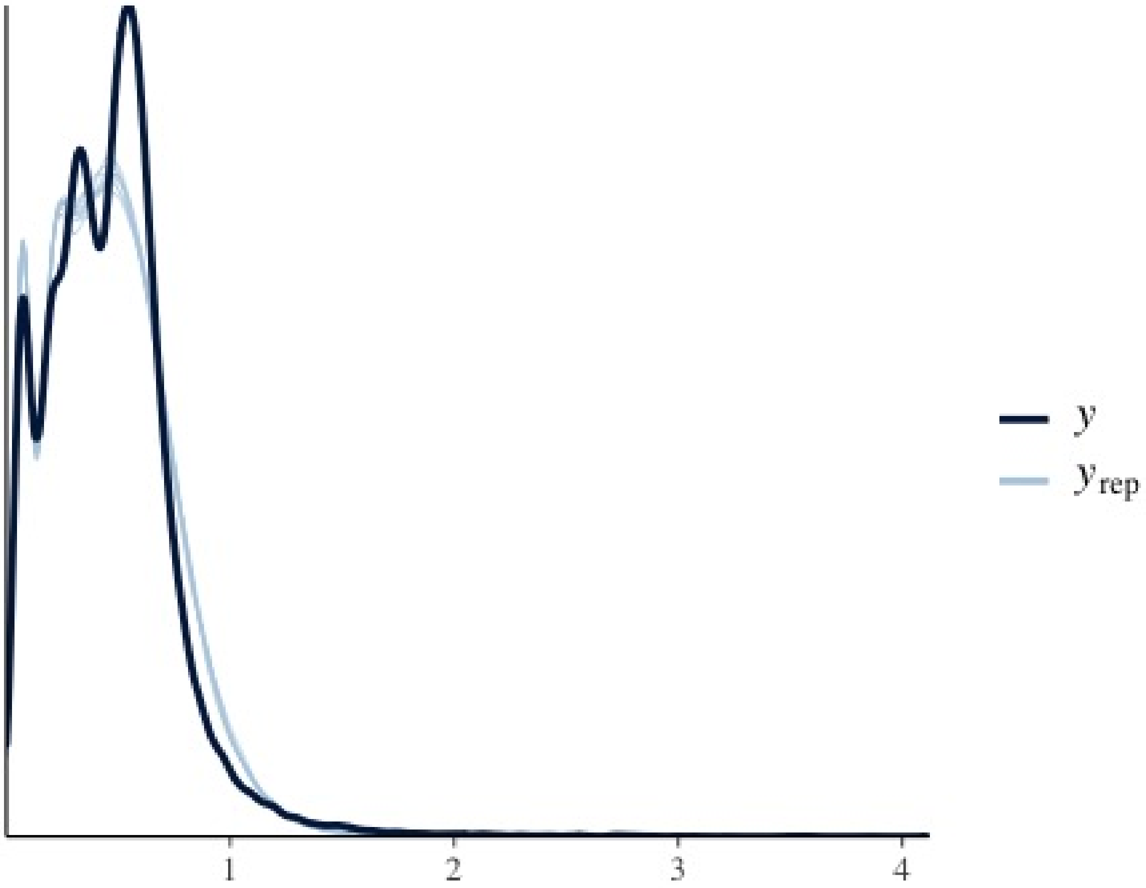
- sdm-TMB - run all the models with and without spatial effects - get started on this (after looking into modes - next point)

- Figure out what those modes are in the observed weight data (pp_check) - are they ages 1,2, and 3?

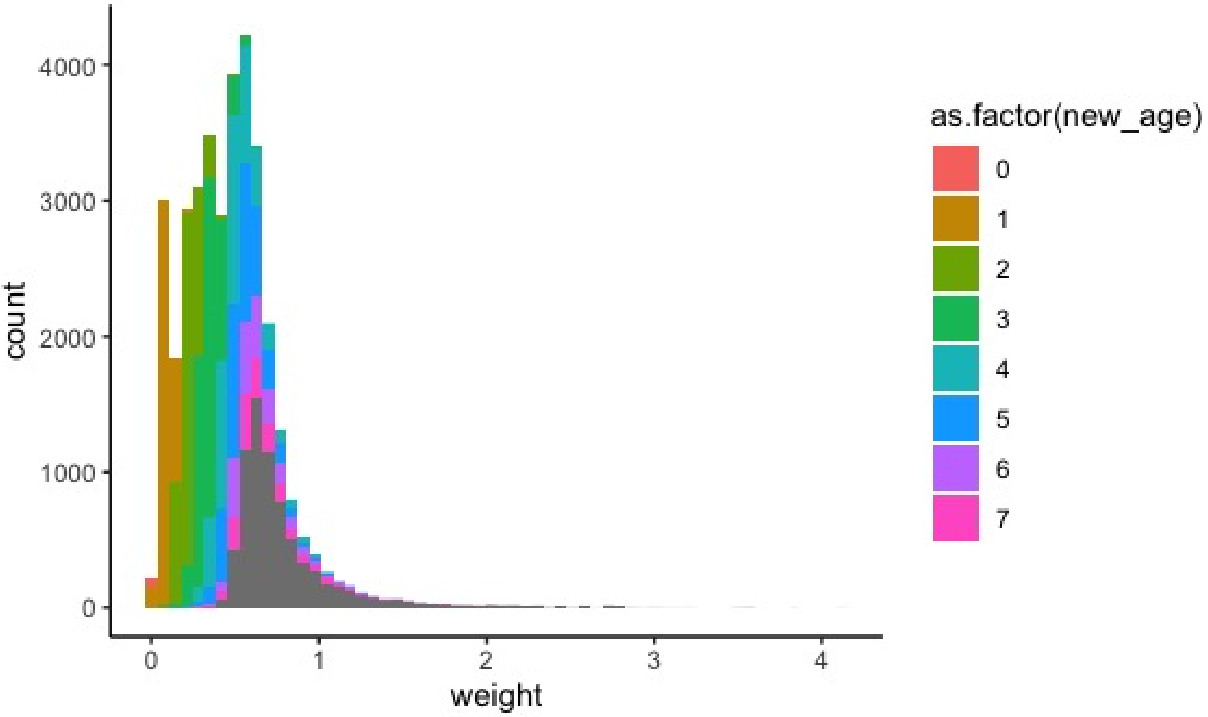
- Motivations for population dynamics fellowship
  - Lay the groundwork for what we might build into a forecast (so instead of interpolating, we can extrapolate)
  - They want to include an internally estimate weight at age into FIMS, and so this work can directly inform how they do that

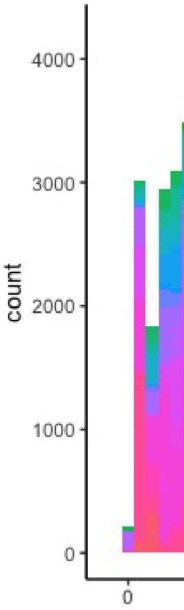
Fixed the distribution from gaussian to lognormal and re-ran the 4 models in brms. 1. Just age as a predictor
2. age with catch_year random effect
3. age with cohort random effect
4. age with both catch_year and cohort random effect

The posterior predictive check is much better when using the lognormal distribution, but there seems to be some bias in predictions as shown by the offset peaks.



So, what are those peaks? Through some simple visualisation, it looks like the peaks are associated with ages as opposed to cohorts. The first peak is the age 1 individuals, the second peak is ages 2 and 3, and the third peak is a compilation of the rest of the ages.

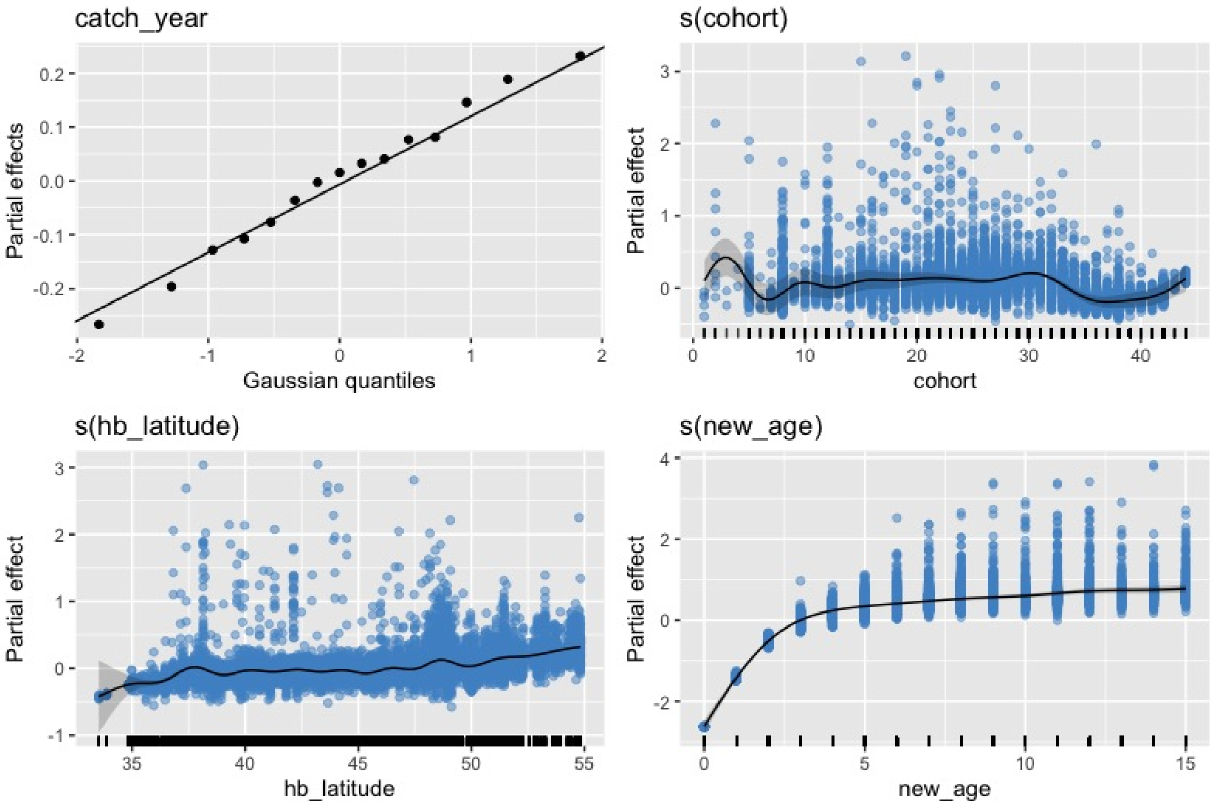




Now I am on a quest to minimize the bias!

I am instead running more gams in mgcv since that has been much faster. In terms of the bias in the posterior predictive check, I originally thought a gamma distribution might be a better fit than the lognormal, but that doesn't seem to be the case when I looked at the outputs and GCV which is a leave one out cross-validation that acts similarly to the AIC. So, I continue to use a lognormal (or at least in the gam case, I am using a gaussian with log link - which hopefully is fine... couldn't find the lognormal distribution option in mgcv)

I also included a smoother on latitude to hopefully capture some of the residuals in the larger fish. Below is a plot of the partial effects for the gam with catch_year random effects, s(cohort), and s(latitude) and you can see the new_age is still underpredicting for those older ages



I also learned about new diagnostic checks using `gam.check` to determine if the number of knots is too low (predictors with k > 1 or a significant p-value)

Aug 8-13, 2022

Following the gams fit last week and the significance of at least a smoother on latitude, I am making the switch to sdm-TMB and going to start figuring out how to use it.

- check correlation structure

Notes on coordinate system for sdmTMB

- have to convert from LatLong to UTM which minimizes distortion and has attributes that make estimating distances easy and more accurate.

- Pacific Northwest is UTM zone 10 (EPSG: 32610)

I was on vacation from Thursday - Monday

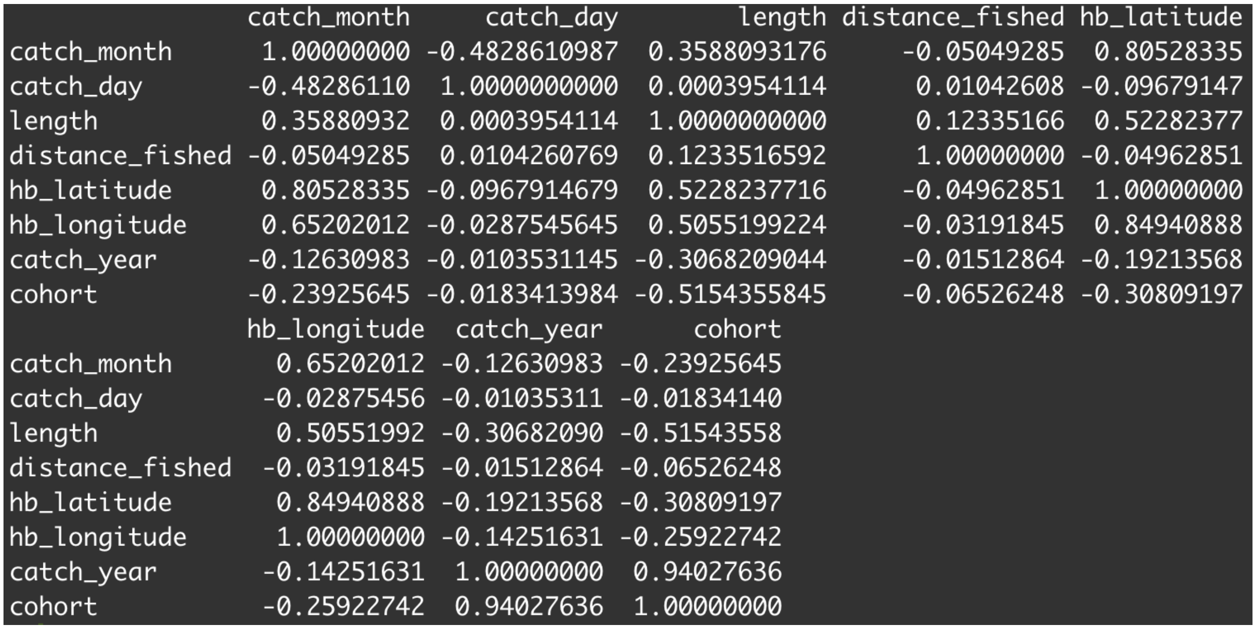
Aug 16-19, 2022

The first thing I did was check correlation structure among key predictors from the data frame which included catch month, catch day, length, distance fished, latitude, longitude, catch year and cohort. Using the `cor()` function, there were a few correlations > 0.7.

- latitude x catch month = 0.80

- latitude x longitude = 0.85

- cohort x catch year = 0.94



```
                catch_month     catch_day        length distance_fished hb_latitude
catch_month      1.00000000 -0.4828610987  0.3588093176     -0.05049285  0.80528335
catch_day       -0.48286110  1.0000000000  0.0003954114      0.01042608 -0.09679147
length           0.35880932  0.0003954114  1.0000000000      0.12335166  0.52282377
distance_fished -0.05049285  0.0104260769  0.1233516592      1.00000000 -0.04962851
hb_latitude      0.80528335 -0.0967914679  0.5228237716     -0.04962851  1.00000000
hb_longitude     0.65202012 -0.0287545645  0.5055199224     -0.03191845  0.84940888
catch_year      -0.12630983 -0.0103531145 -0.3068209044     -0.01512864 -0.19213568
cohort          -0.23925645 -0.0183413984 -0.5154355845     -0.06526248 -0.30809197
                hb_longitude  catch_year      cohort
catch_month       0.65202012 -0.12630983 -0.23925645
catch_day        -0.02875456 -0.01035311 -0.01834140
length            0.50551992 -0.30682090 -0.51543558
distance_fished  -0.03191845 -0.01512864 -0.06526248
hb_latitude       0.84940888 -0.19213568 -0.30809197
hb_longitude      1.00000000 -0.14251631 -0.25922742
catch_year       -0.14251631  1.00000000  0.94027636
cohort           -0.25922742  0.94027636  1.00000000
```

Big picture thinking

1. What are the local and regional trends in weight at age of Pacific Hake
2. Which covariates explain these changes and in what direction do they covary?

3. How strong are the latent spatial and spatiotemporal random effects? (maybe don't explicitly say this, but good to include in results)

4. To what extent does incorporating growth variation into the interpolation of missing data within the stock assessment affect the estimationg of management reference points?

Things to remember

- the data that I have is limited to the months of June - September when the acoustic trawl survey is sampling.

Variability can be partitioned into 4 ways (larsen et al 2001 - Designs for evaluating local and regional scale trends):

- Spatial: areas with increased condition in all years

- Temporal: changes throughout the populations range in a given year

- Spatiotemporal: areas with increased condition in a particular year

- Individual: residual variation in condition for each individual

Covariates to consider

- Temperature (at depth? SST?), PDO, ENSO (abiotic)

- Main food source (Euphasiid) or predator or competition from strong year classes (biotic)

- total catch? (fishing)

Questions for meeting with Kristin

- Do I need to standardize the data according to the CPUE? Saw this in the body condition sdmTMB paper - might just be for density model

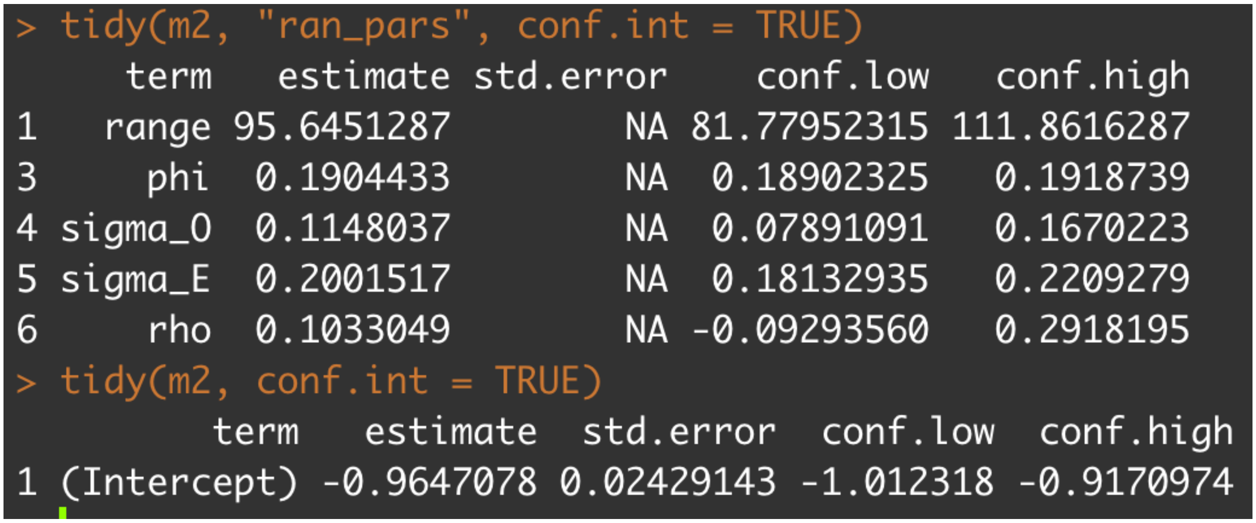
- Were there any changes in the net used for the acoustic-trawl survey that might influence the size of the fish being caught? Vessel-specific variation from year to year as well…

- Should we start to look into obtaining environmental data?
  -biomass at age for strong year classes

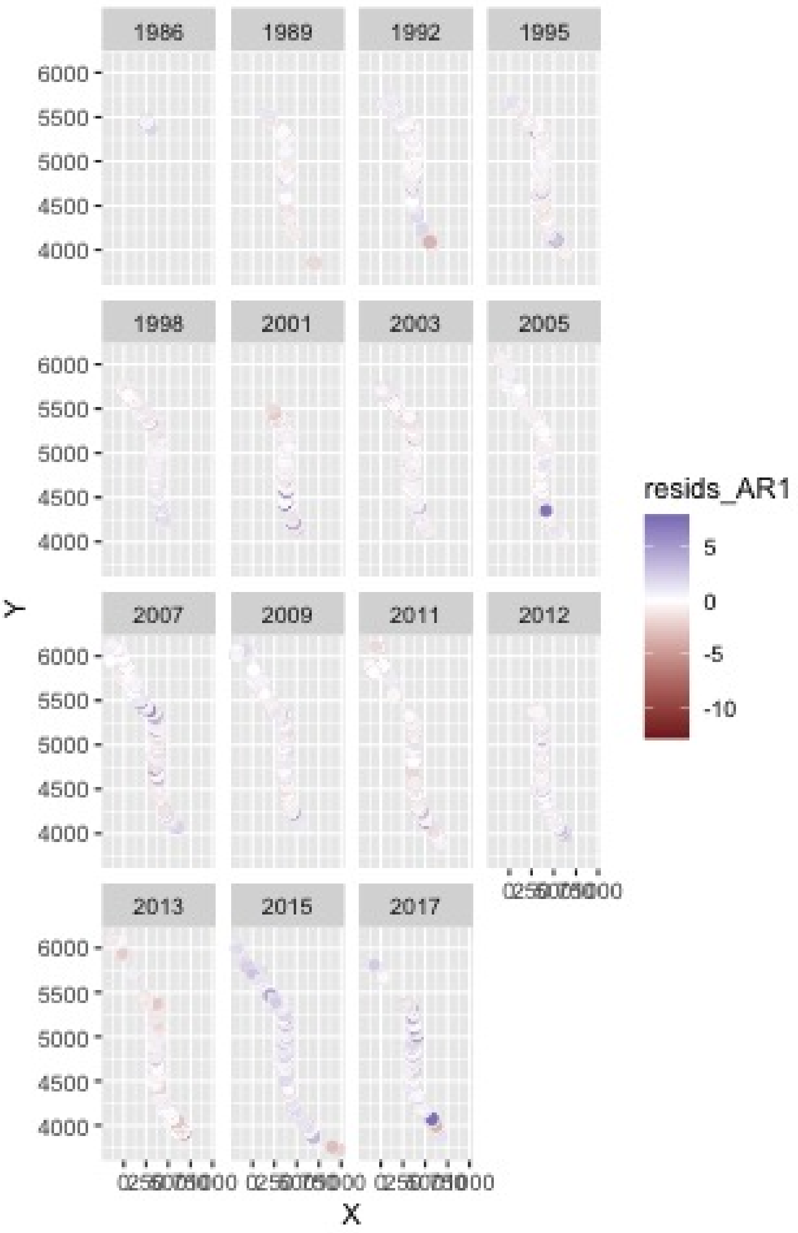
Explorations with sdmTMB

I am getting the hang of it. I started off with a very simple, non-spatial model where weight is predicted by age and cohort, with age and cohort as have a smoothing function. Then I turned on spatial, then the spatiotemporal random effect with an AR1 process. I tested two spatiotemporal models

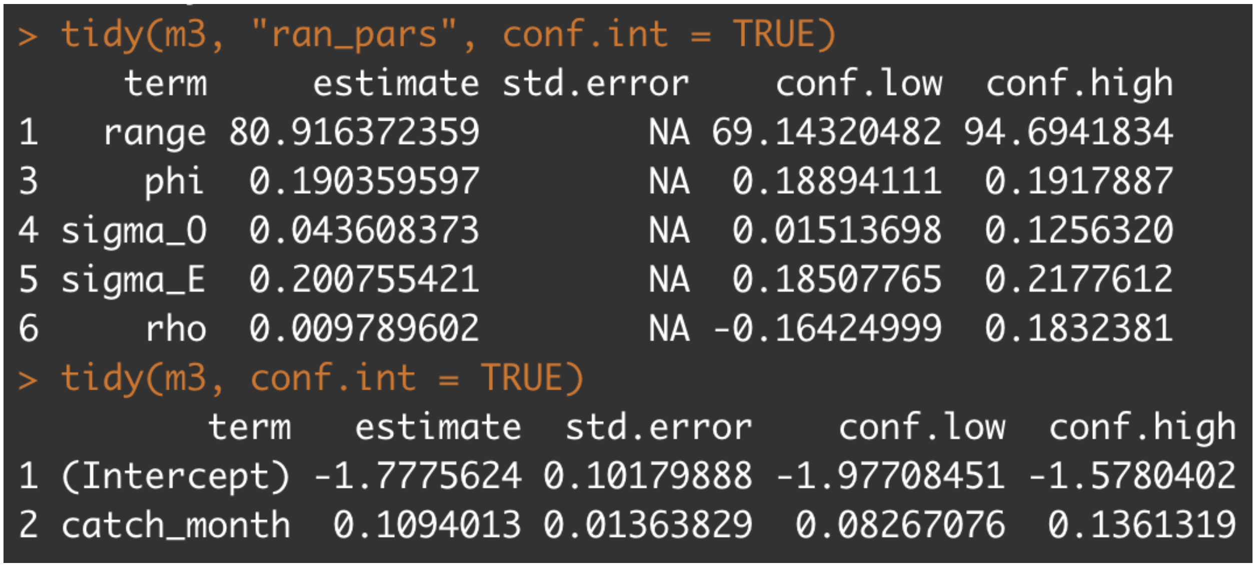
`m2: weight ~ s(age) + s(cohort)`



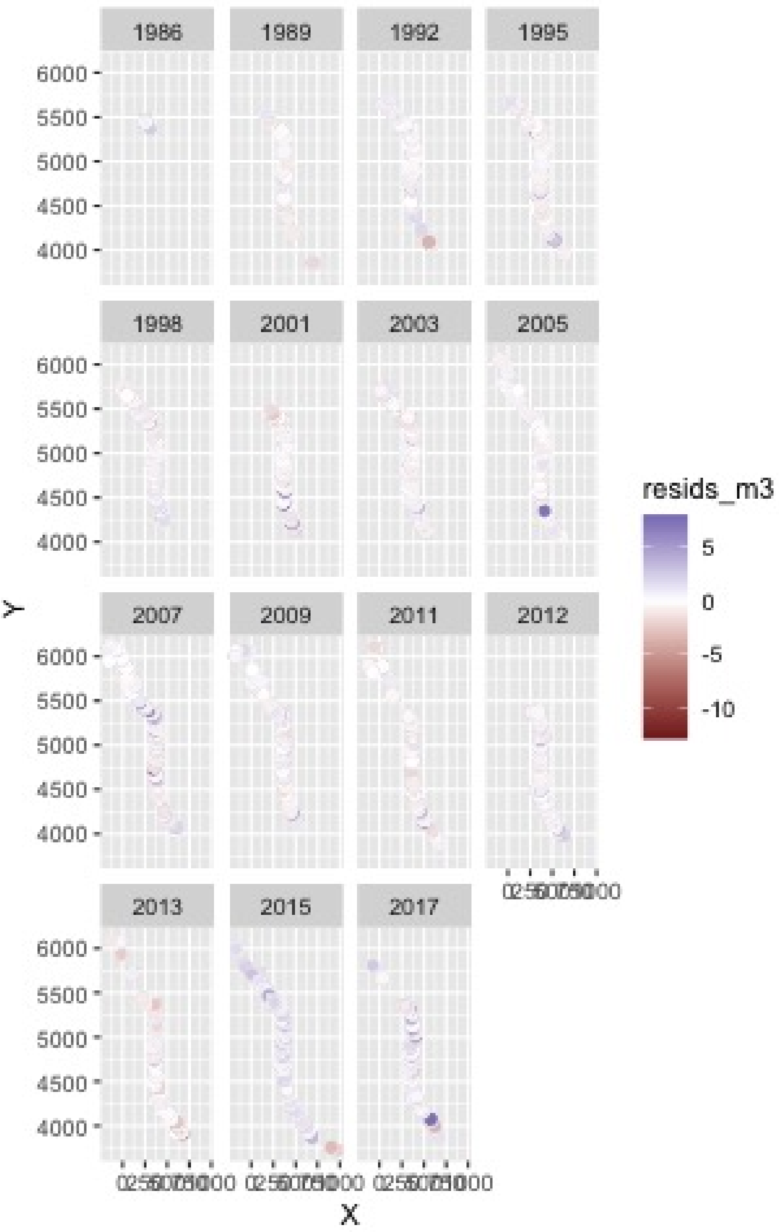
```
> tidy(m2, "ran_pars", conf.int = TRUE)
     term   estimate std.error    conf.low   conf.high
1   range 95.6451287        NA 81.77952315 111.8616287
3     phi  0.1904433        NA  0.18902325   0.1918739
4 sigma_O  0.1148037        NA  0.07891091   0.1670223
5 sigma_E  0.2001517        NA  0.18132935   0.2209279
6     rho  0.1033049        NA -0.09293560   0.2918195
> tidy(m2, conf.int = TRUE)
         term   estimate  std.error  conf.low  conf.high
1 (Intercept) -0.9647078 0.02429143 -1.012318 -0.9170974
```



```
m3: weight ~ s(age) + s(cohort) + catch_month
```

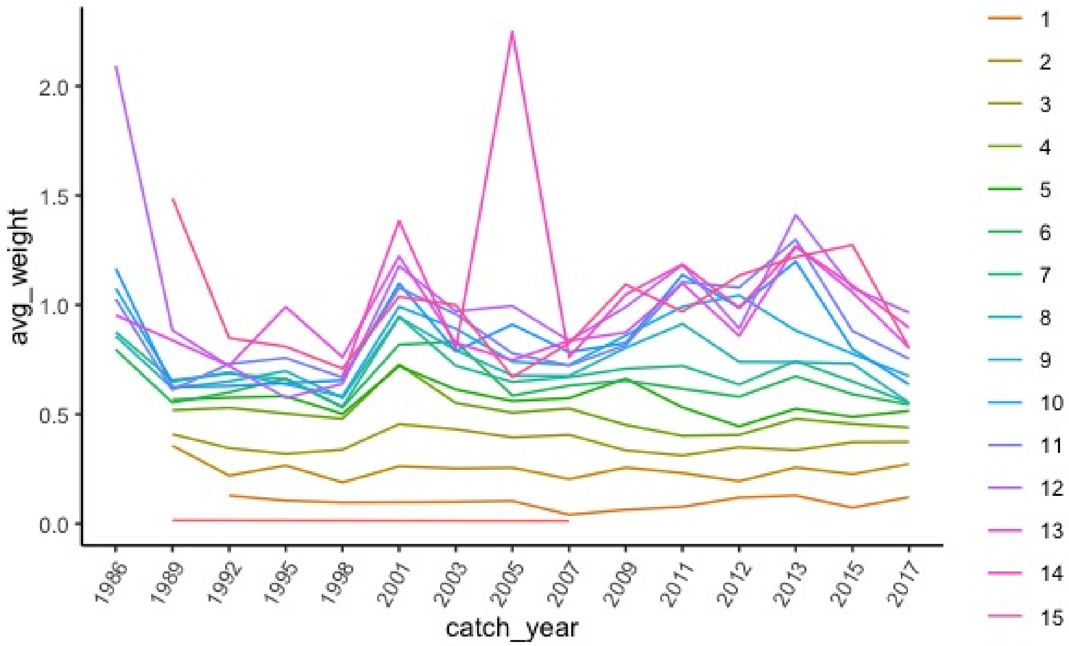


```
> tidy(m3, "ran_pars", conf.int = TRUE)
     term    estimate std.error   conf.low  conf.high
1   range 80.916372359        NA 69.14320482 94.6941834
3     phi  0.190359597        NA  0.18894111  0.1917887
4 sigma_O  0.043608373        NA  0.01513698  0.1256320
5 sigma_E  0.200755421        NA  0.18507765  0.2177612
6     rho  0.009789602        NA -0.16424999  0.1832381
> tidy(m3, conf.int = TRUE)
         term   estimate  std.error    conf.low  conf.high
1 (Intercept) -1.7775624 0.10179888 -1.97708451 -1.5780402
2 catch_month  0.1094013 0.01363829  0.08267076  0.1361319
```

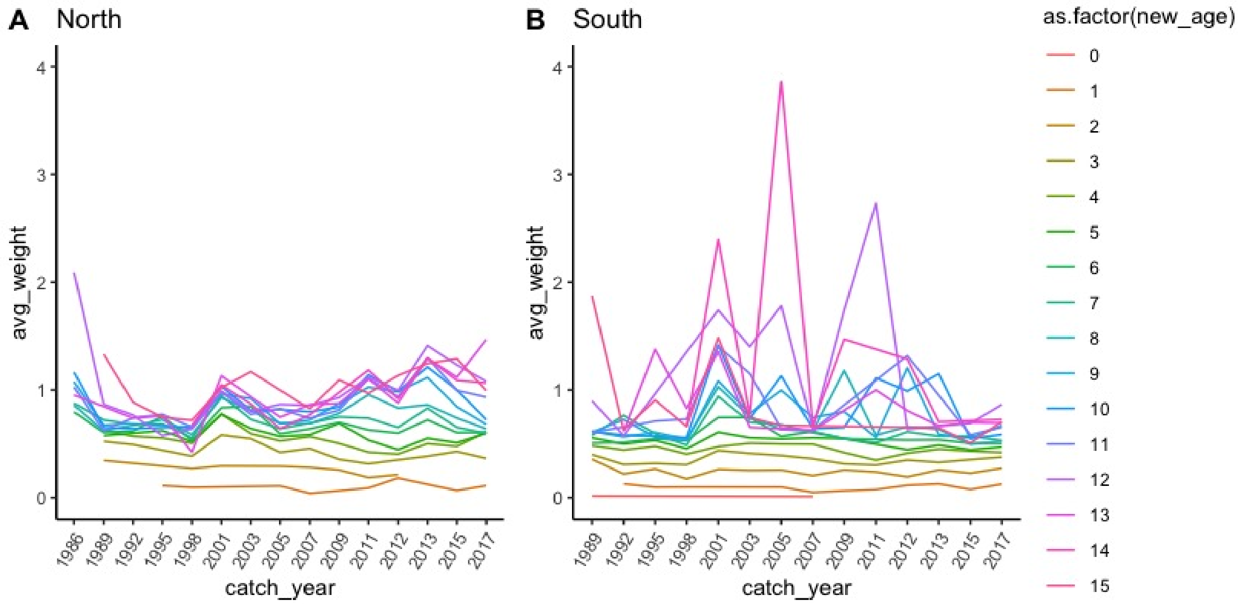


Catch month and latitude have a correlation of 0.8. Is it fine to still include if latitude is not considered a predictor, but rather a spatial random effect?

In terms of autocorrelation, I realize I never really looked at the time series of weight for each age to see if there are any long term declines or where the variability is most prominent.



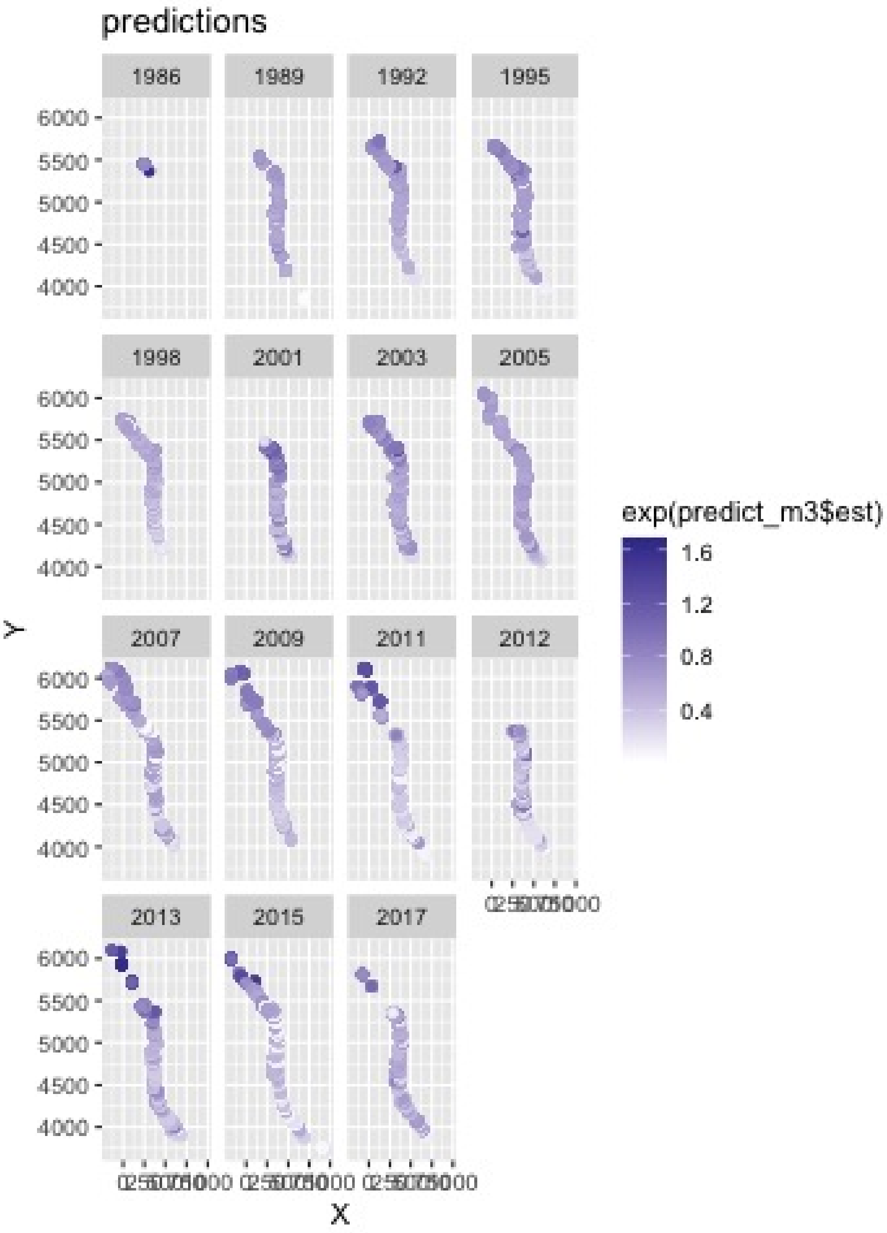
There also seems to be some differences when we split the data between north and south at the median point. UTC 4957.963

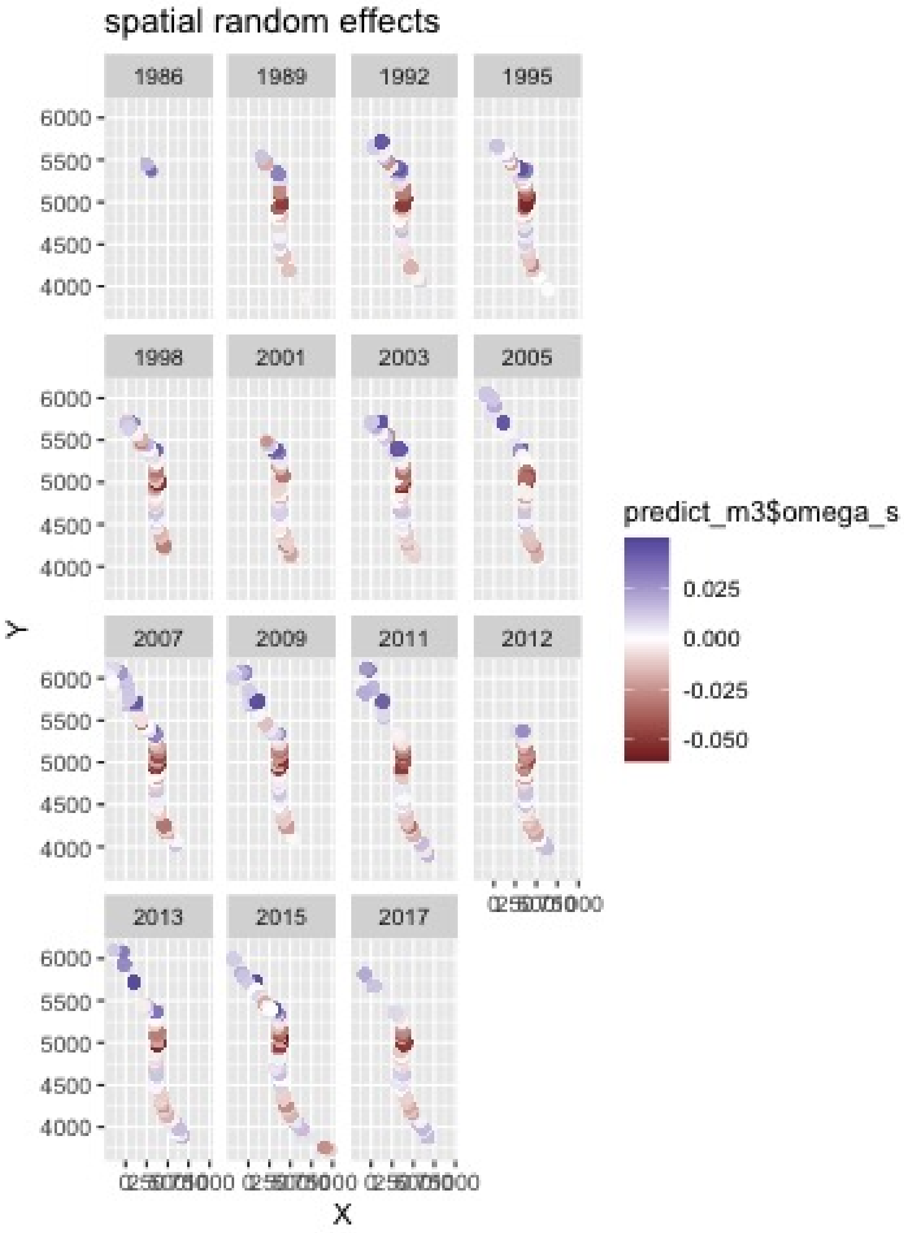


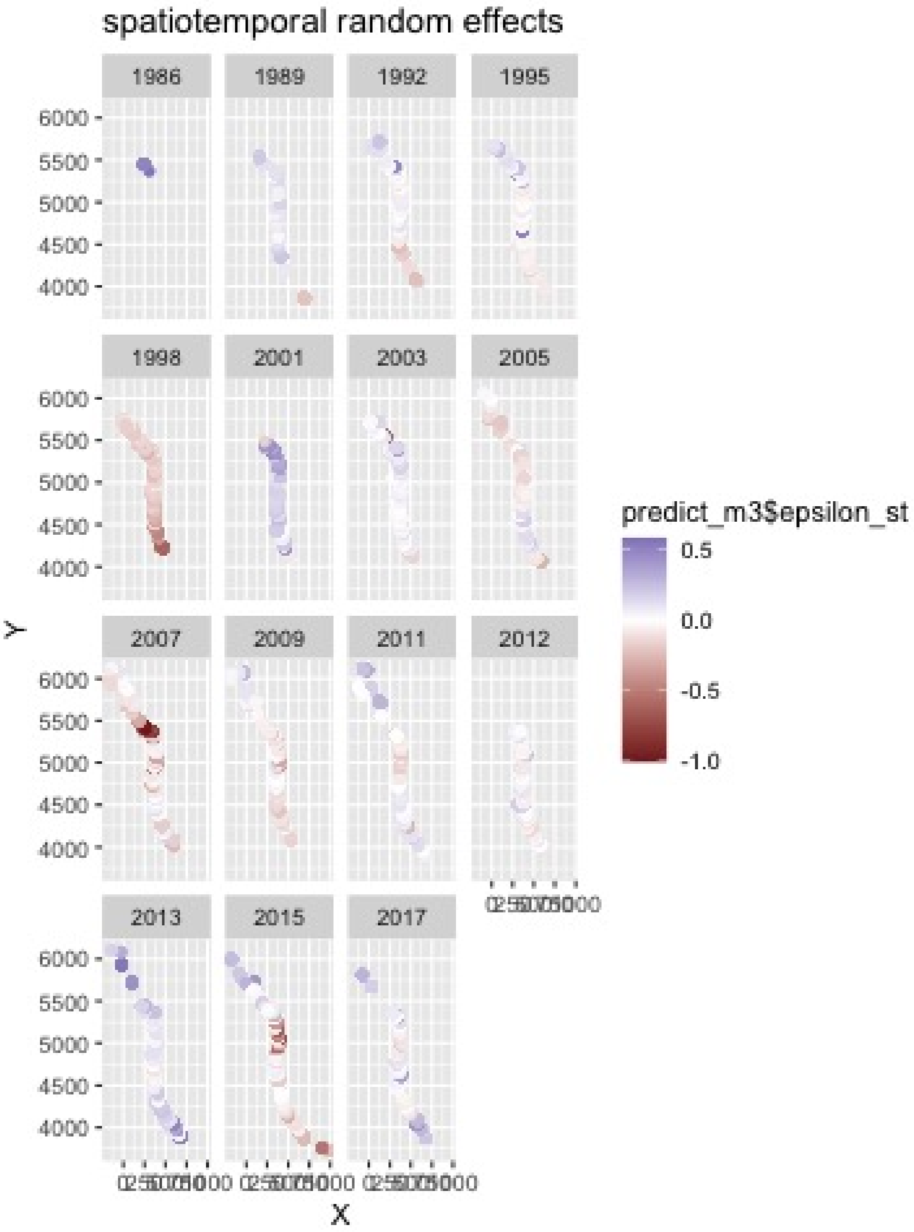
There is much greater variability in the older age classes of the south. Moreover, there may be a slightly increasing trend in the north.

Definitely worth looking at a longer time series of this - where is the fishery data again?

Now looking at the outputs of m3


predictions
1986
1989
1992
1995
1998
2001
2003
2005
2007
2009
2011
2012
2013
2015
2017
6000
5500
5000
4500
4000
Y
X
0250500750000
exp(predict_m3$est)
1.6
1.2
0.8
0.4


spatial random effects
1986
1989
1992
1995
1998
2001
2003
2005
2007
2009
2011
2012
2013
2015
2017
6000
5500
5000
4500
4000
Y
X
0 250 500 750 1000
predict_m3$omega_s
0.025
0.000
-0.025
-0.050



Next week:

- time varying intercept model and compare to gams
- add a smoother on catch_year
- biomass of cohort in that year rather than cohort

Aug 22-29, 2022

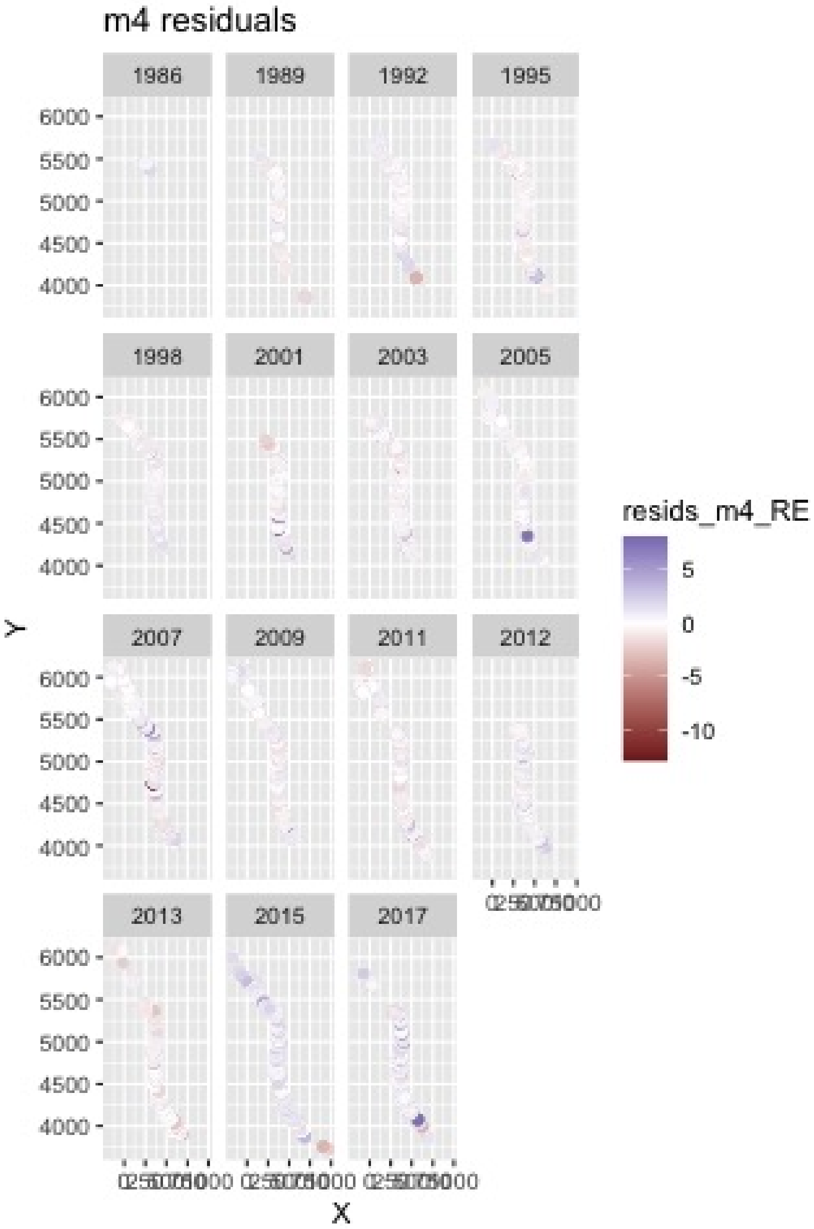
There are a few ways to include time-varying intercepts

- as.factor(year) I tried this and the model didn't converge very well
- (1 | year) I tried this as well and the model didn't converge very well

- time_varying = ~ 1 This one worked the best. It follows a random walk

```
m4 = weight ~ 0 + s(new_age) + s(cohort) + catch_month with time-varying intercept
```

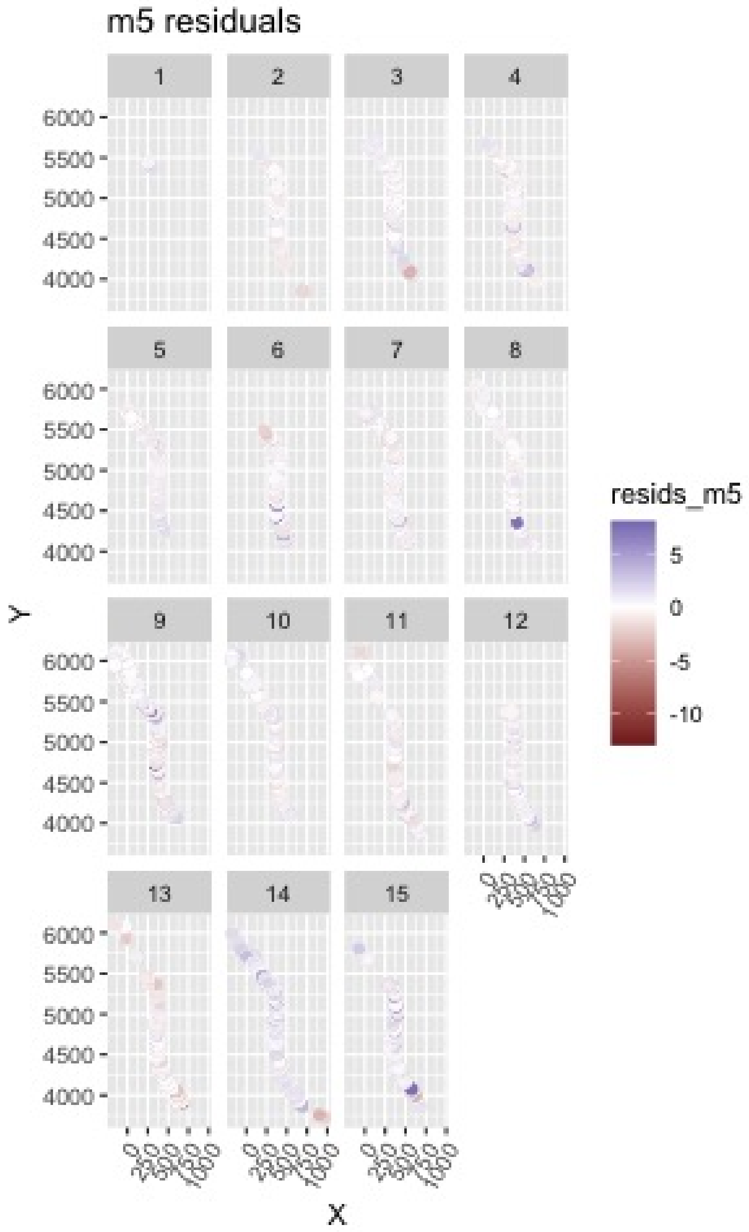
However, it doesn't look like it improved the residuals very much…



Could it be that one of the predictors is time-varying rather than the intercept?

I also tried including a smoother on catch_year in addition to the time-varying intercept and that doesn't seem to capture the differences in weight in 2013-2015

```
m5 = weight ~ 0 + s(new_age) + s(cohort) + catch_month + s(catch_year) with a time-varying
intercept
```



Also tried a model that didn't include a smoother on catch year but instead created a separate slope for the smoother on new_age. I did this because I was hoping to capture the variability in more recent years that we saw in the observed weight at age in the north above.

Potentially include age as a time-varying slope to account for the changes in weight at age in more recent years? unfortunately can't include smoothers in the time-varying argument, but instead can use independent slopes for each year s(new_age, by = catch_year)

```
m6 = weight ~ 0 + s(new_age, by = catch_year)  + s(cohort) + catch_month with time-varying
intercept
```

This model did not converge (non-positive Hessian definite)

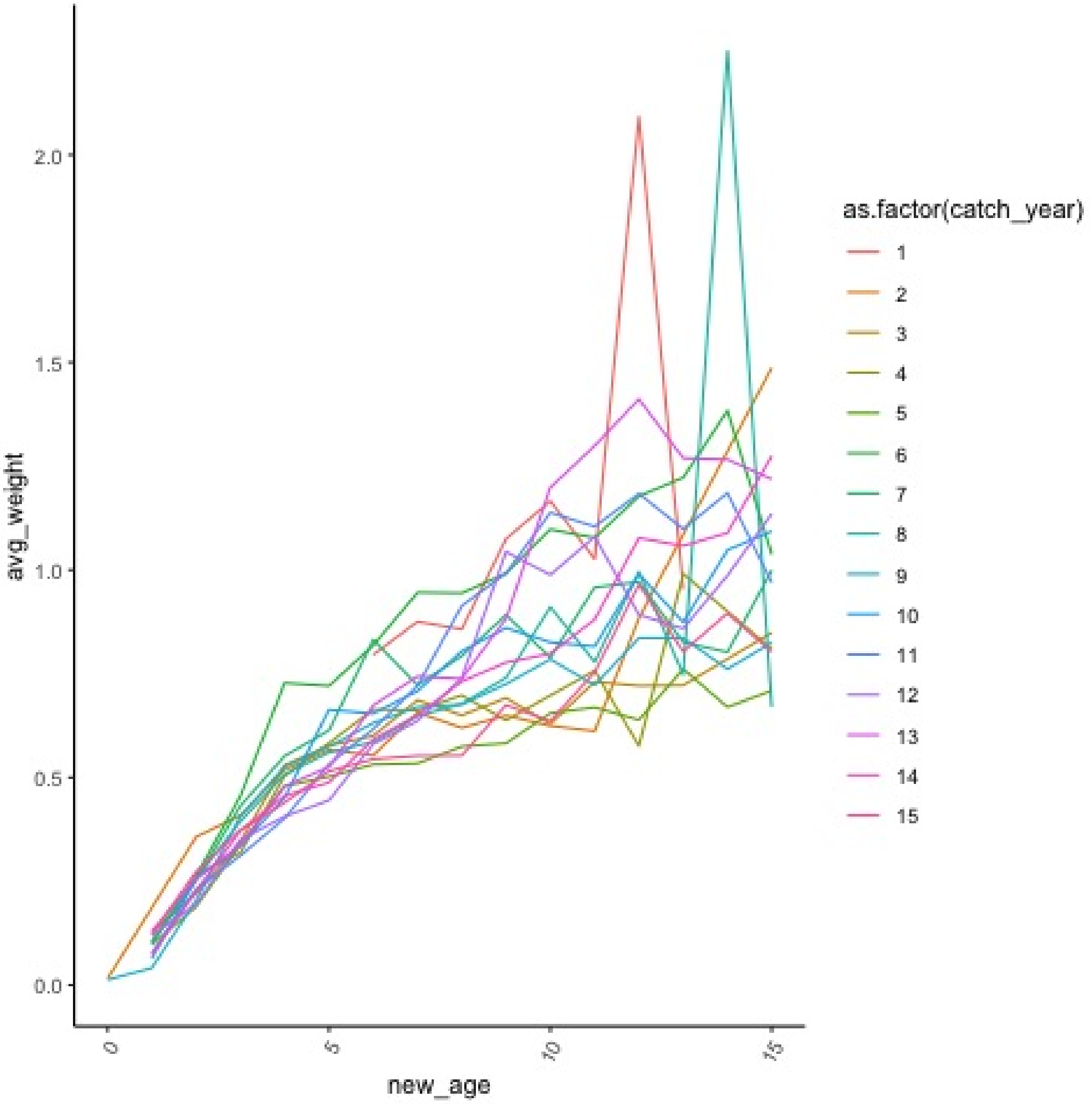
Tried removing the smoother on cohort,

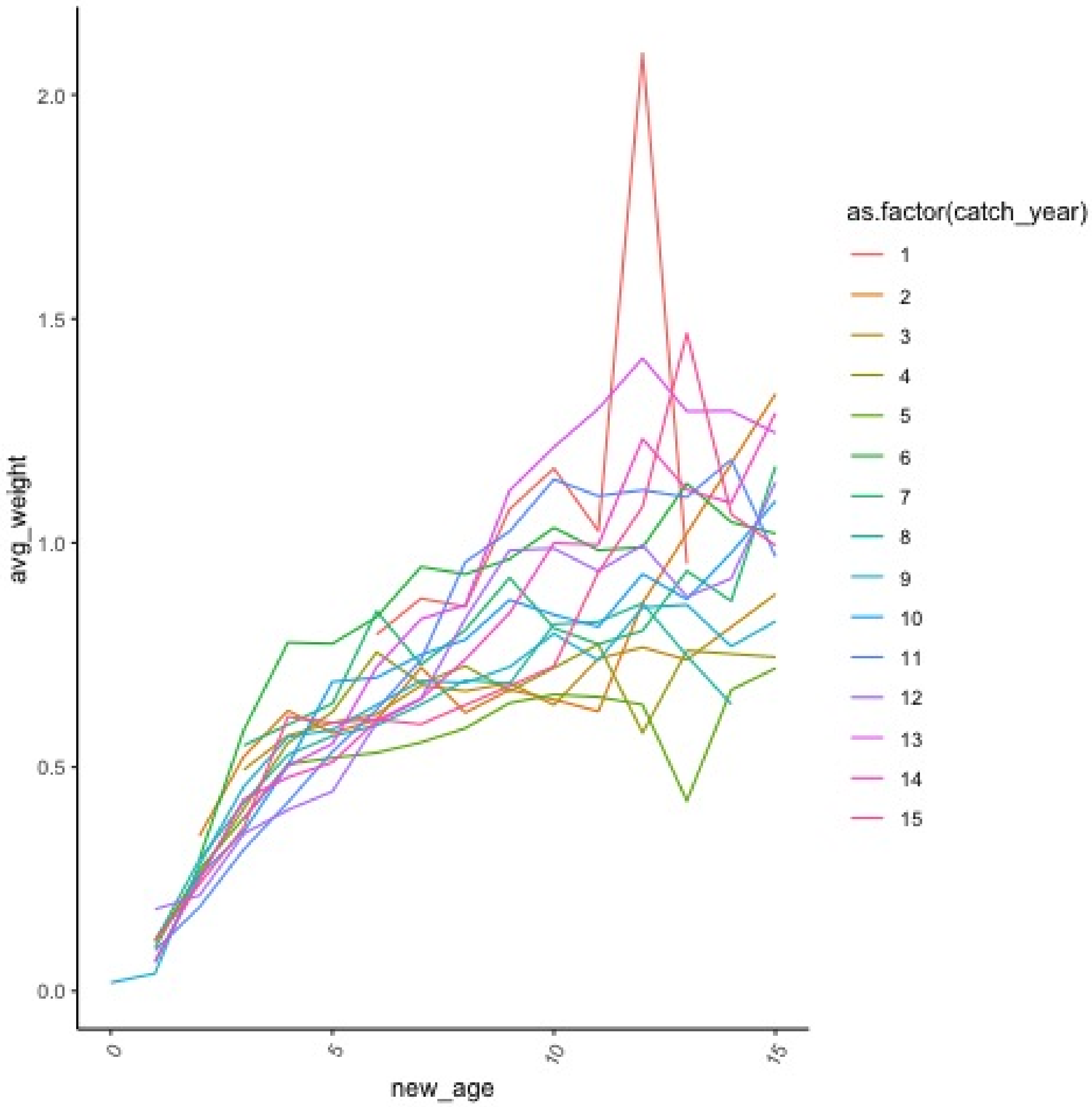
```
m7 =  weight ~ 0 + s(new_age, by = catch_year) + catch_month with time-varying intercept
```

This model converged, but it still doesn't capture the residuals in the more recent years.

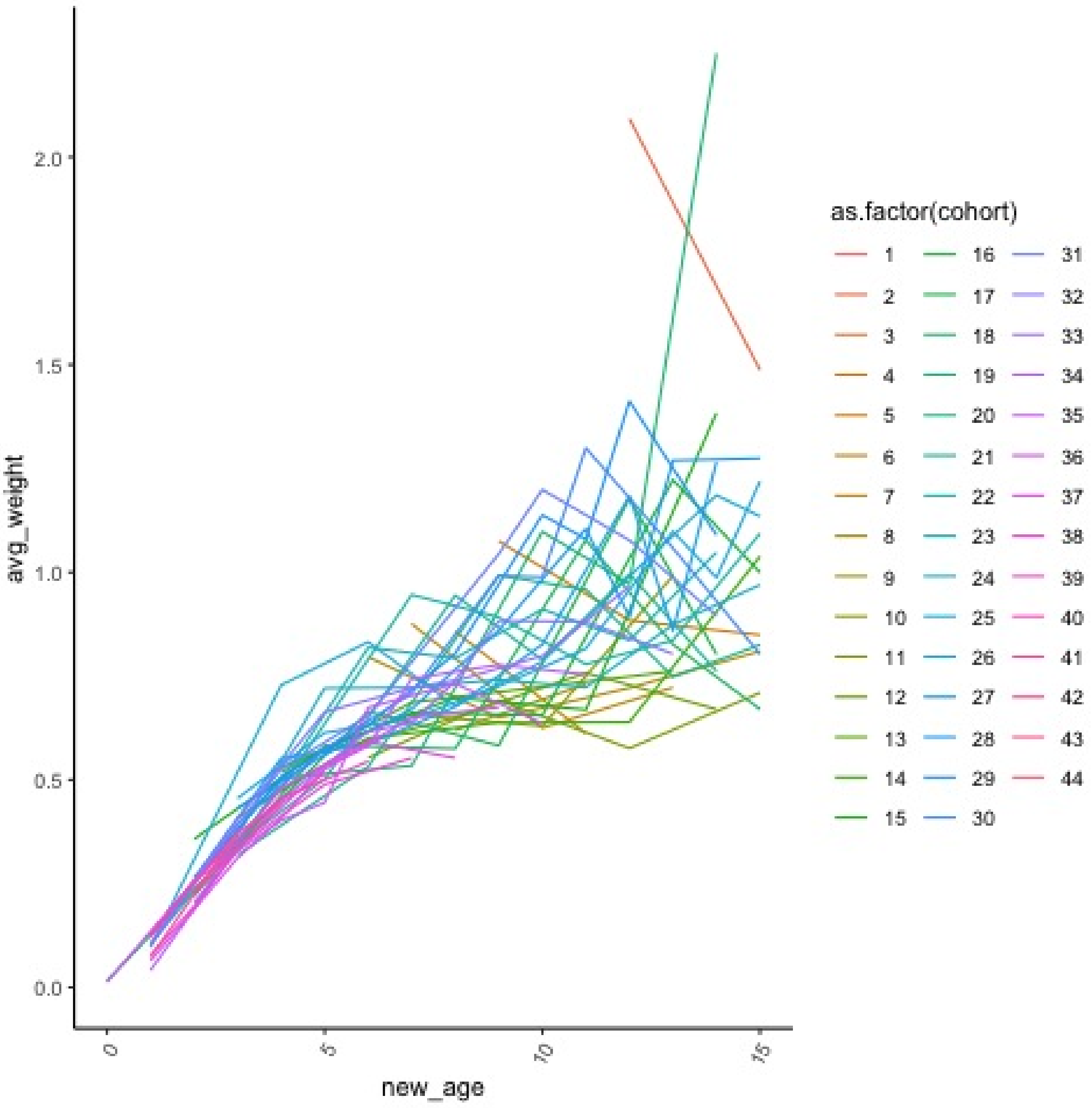
Also, realized the maximum residual is "Inf". I just don't think any of these models are doing too well, so I am stepping back and looking at the data once again.

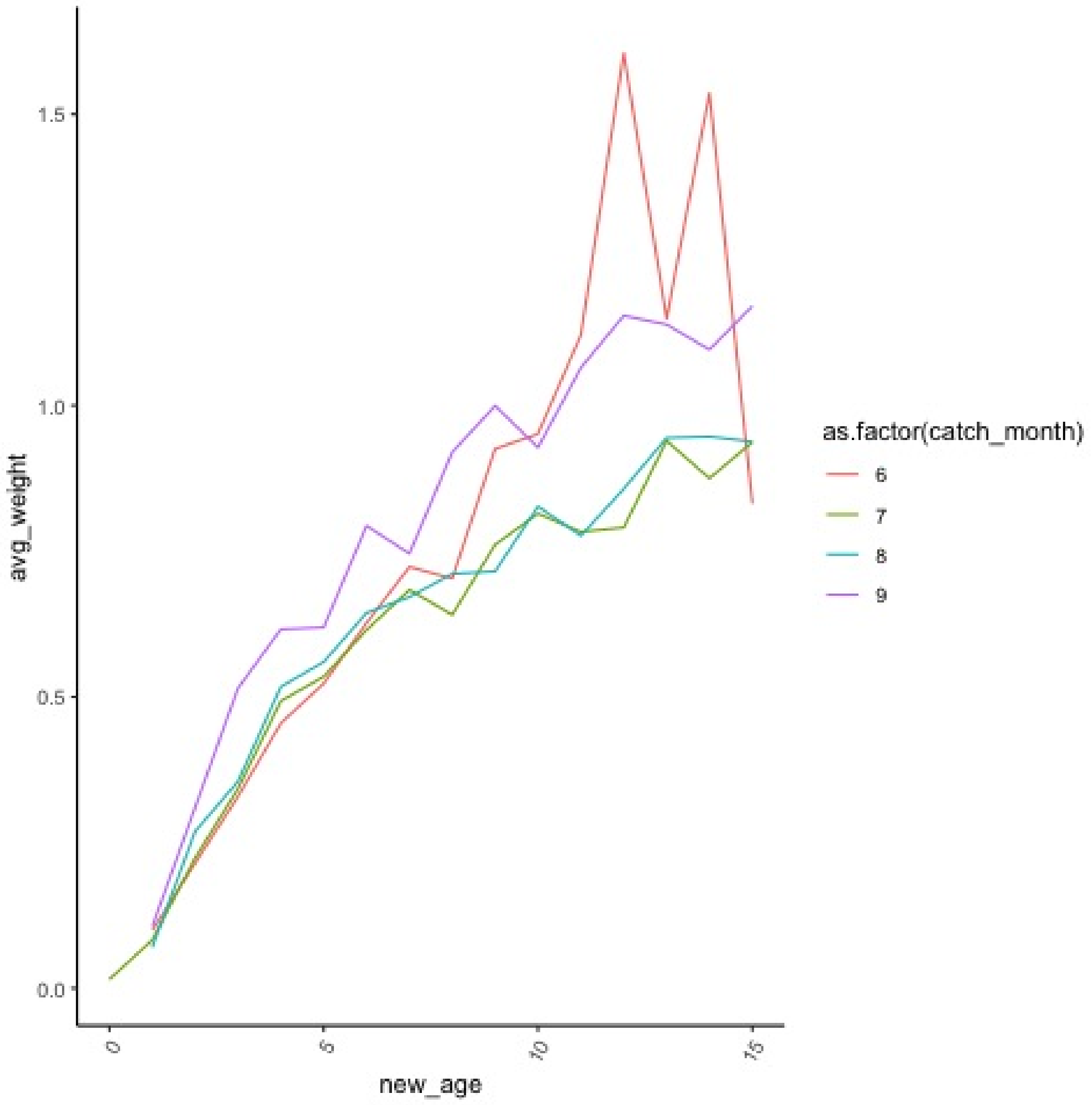
This first plot is weight at age curves by year. and the next one is just for the northern individuals.



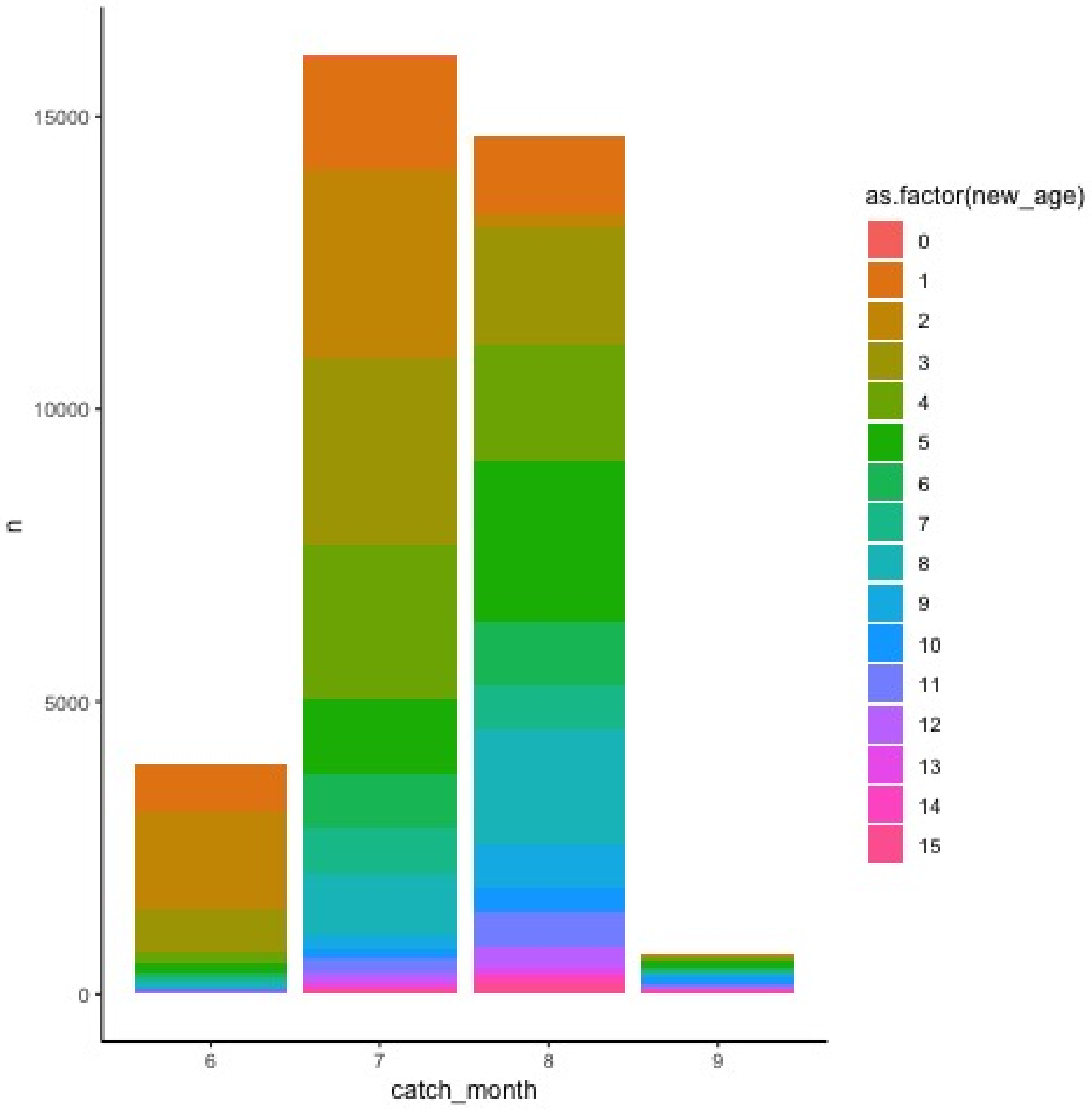


Then, by cohort

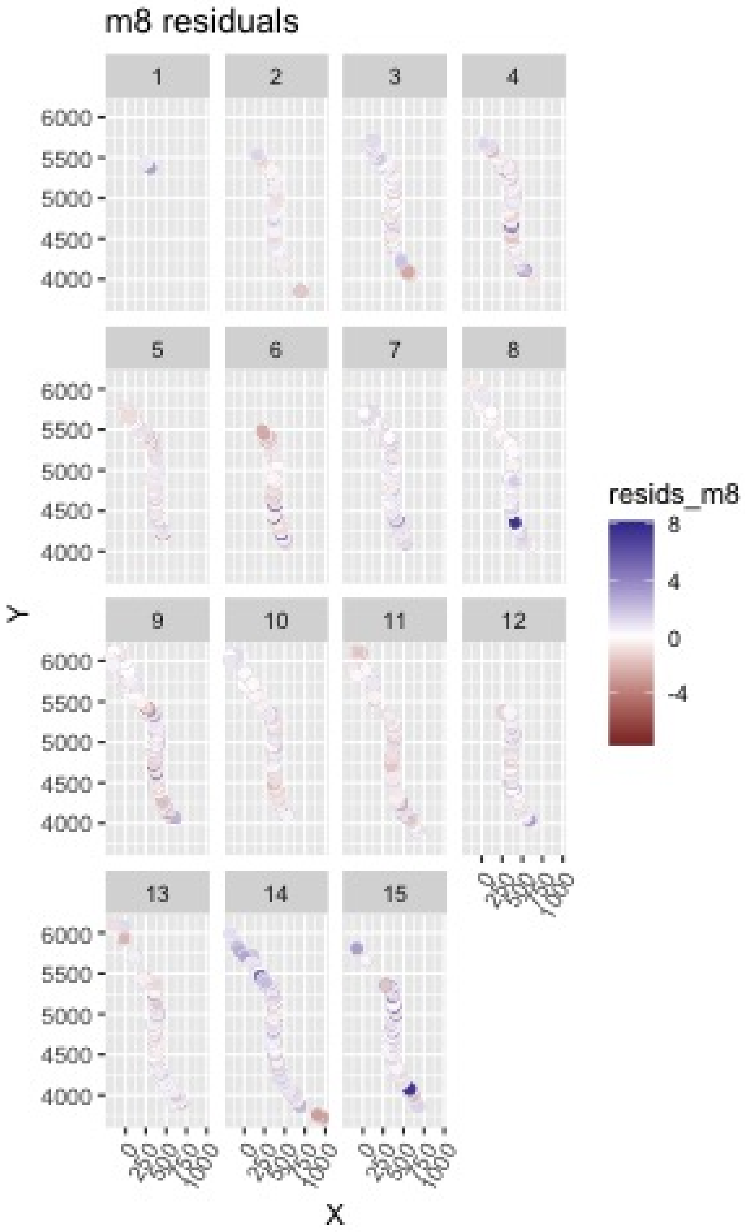

avg_weight
0.0
0.5
1.0
1.5
2.0
new_age
0
5
10
15
as.factor(cohort)
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44



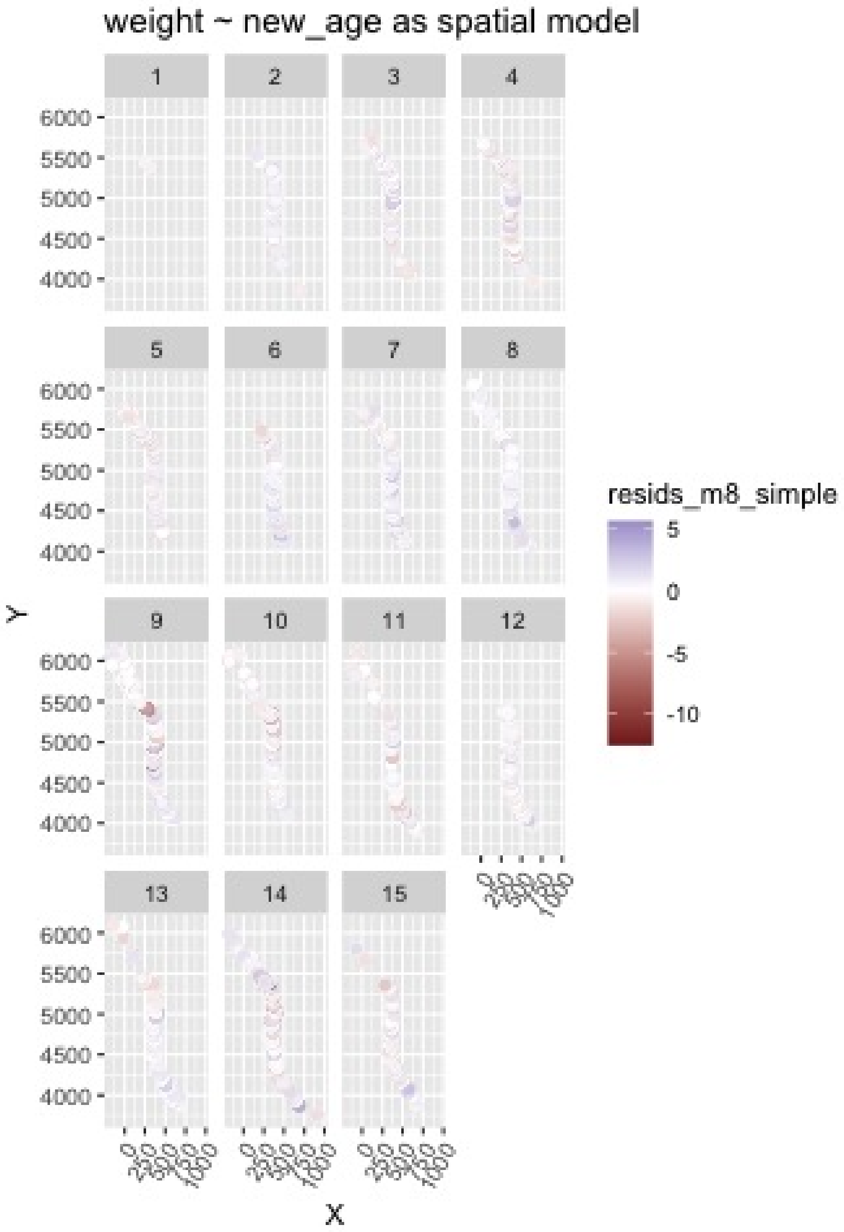
But as a caveat, here are how many observations of each age are sampled per month. Month 6 and 9 are very lightly sampled, so take with caution.



`m8 = weight ~ s(new_age, by = catch_year)` Just spatial (not spatiotemporal)



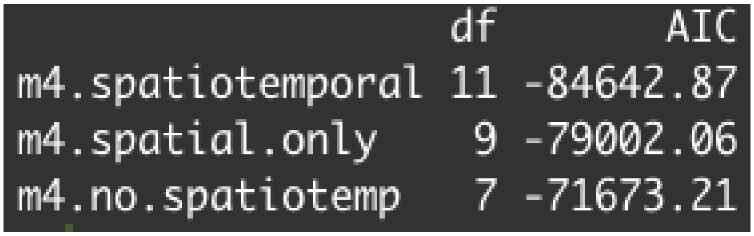
Okay, but even simpler, the spatial model with `weight ~ new_age` seems to minimize the residuals quite a bit.



Meeting with Kristin
- catch_month currently is a fixed linear effect, but the data tell us otherwise. Maybe best to consider it as a random effect
- Does it need the spatial part or the spatiotemporal part or either? - what are the temporal trends and potential covariates (qualitatively)
- standard deviation of the catch month random effect vs intercept, vs others to see how much those matter compared to the spatiotemporal.
- try to fit catch_month random effect, and then add the time-varying (but potentially confounded)
- sub-areas within a region - weight-at-age curve for canadian vs US
- fishery data - can't fit spatial model, but we know that the canadian fishery fishes in canada and the us fishery fishes in US, so we can at least have that spatial component (which for the MSE is relevant)
- malick - relationships with temperature.

Sept 12-16, 2022

Prior to this week, I have settled on a model `weight ~ 0 + s(new_age) + s(cohort) + (1 | catch_month) + (1 | catch_year)` and have tried three versions: spatiotemporal, spatial, and without random fields.



```
                    df       AIC
m4.spatiotemporal 11 -84642.87
m4.spatial.only    9 -79002.06
m4.no.spatiotemp   7 -71673.21
```

According to AIC, the spatiotemporal model was the best model. It also converged very nicely.

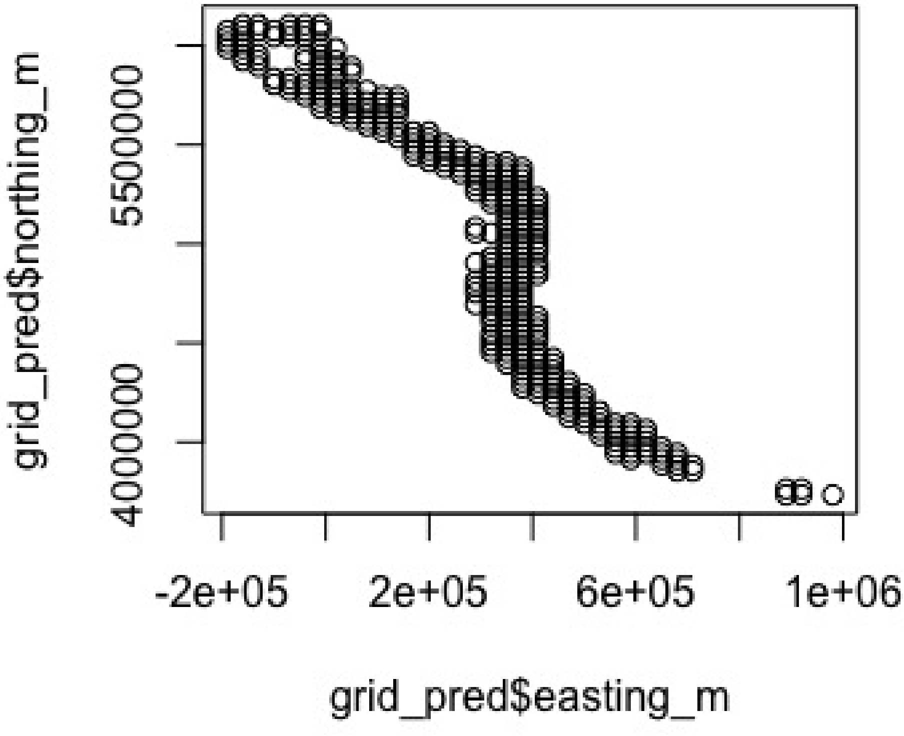
Questions for Kristin

1. how to make a mesh over the survey area?

- plot the random effect levels for the catch_month -github action knit rmarkdown

Sept 19-23, 2022

Trying to learn how to create a spatial domain, following code that Malick provided (in the `malick_code` folder of the project).



I was able to make a spatial domain following Michael Malick's code, however, when I go to make predictions on those new data, an error pops up saying

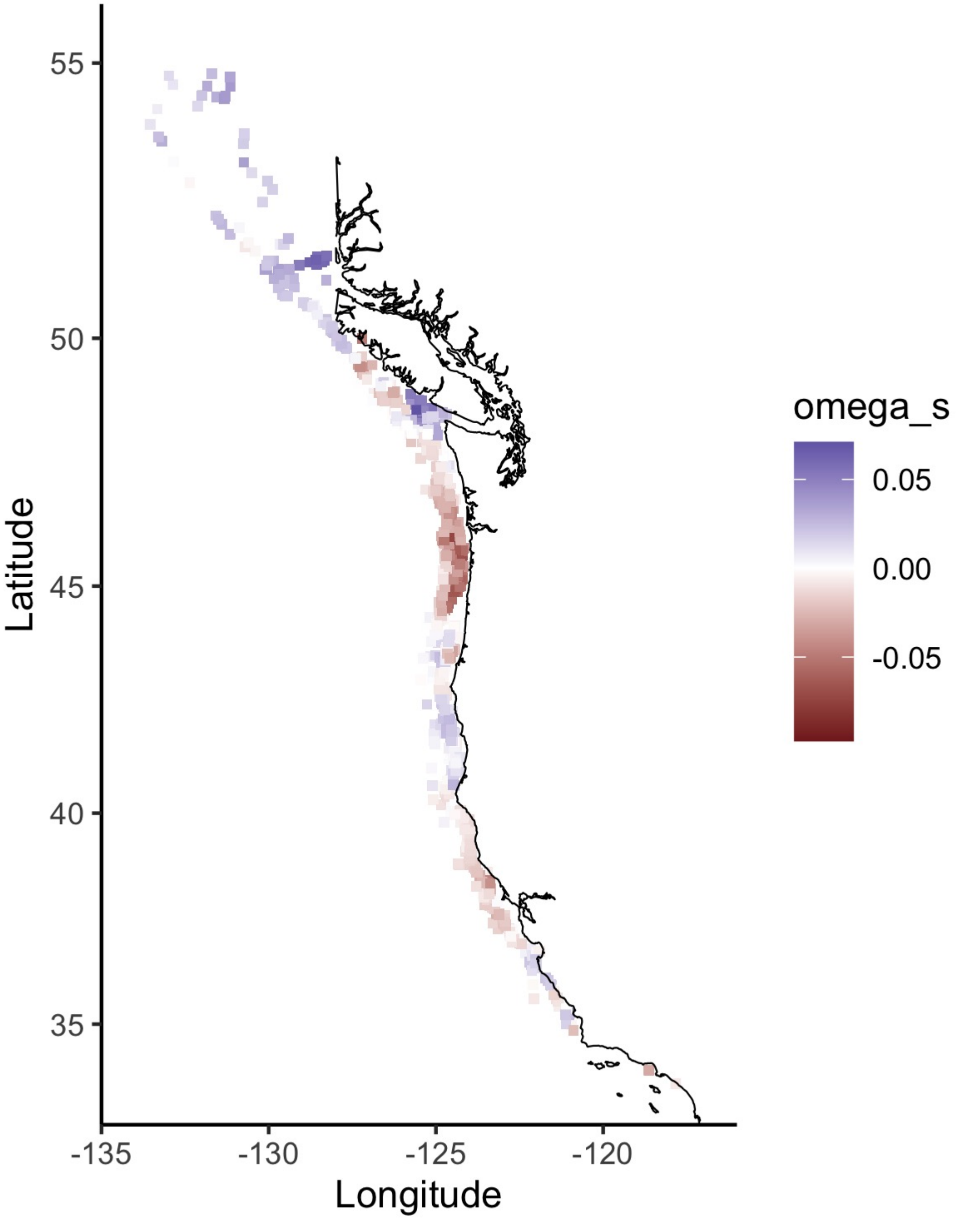
Error in vapply(RE_names, function(x) as.integer(nd[[x]]) - 1L, rep(1L, : values must be length 4575, but FUN(X[[1]]) result is length 0

I tried reformatting the dataset, making sure that the UTM coordinates were aligned and that time was modeled (i.e. can't be considered as a factor class). Not entirely sure what else it could be. Either way, decided to continue making maps using the observed datapoints.

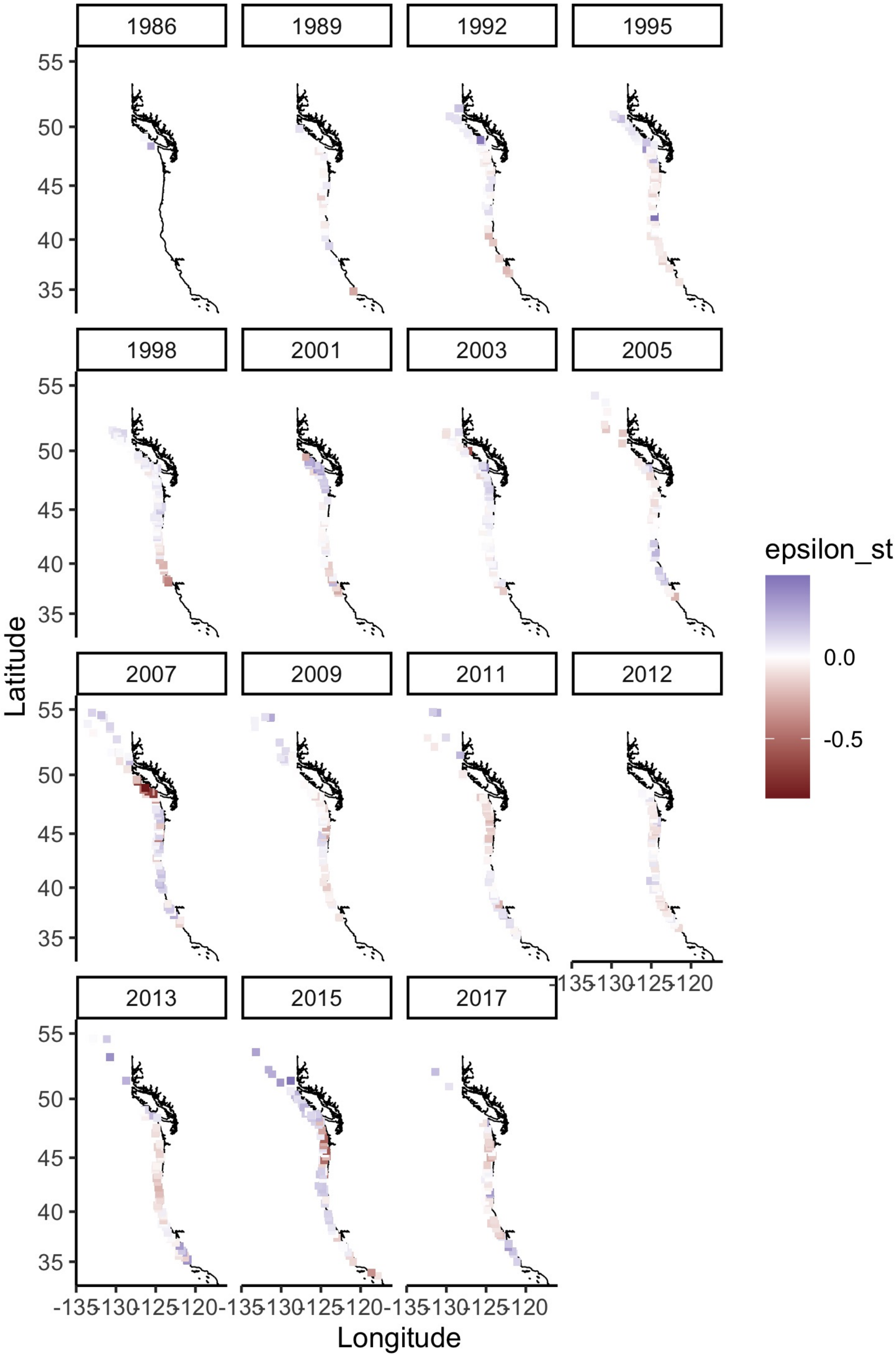
Because time needed to be modeled (not considered a factor class), I had to restructure my model. It still had spatial and spatiotemporal random effects.

`weight ~ 0 + s(new_age) + s(cohort) + (1 | catch_month)` with time-varying intercept (~ 1) following a random walk.

I overlayed some of the predictions over the map of the coastline and some interesting patterns arise, especially with spatial random effects.

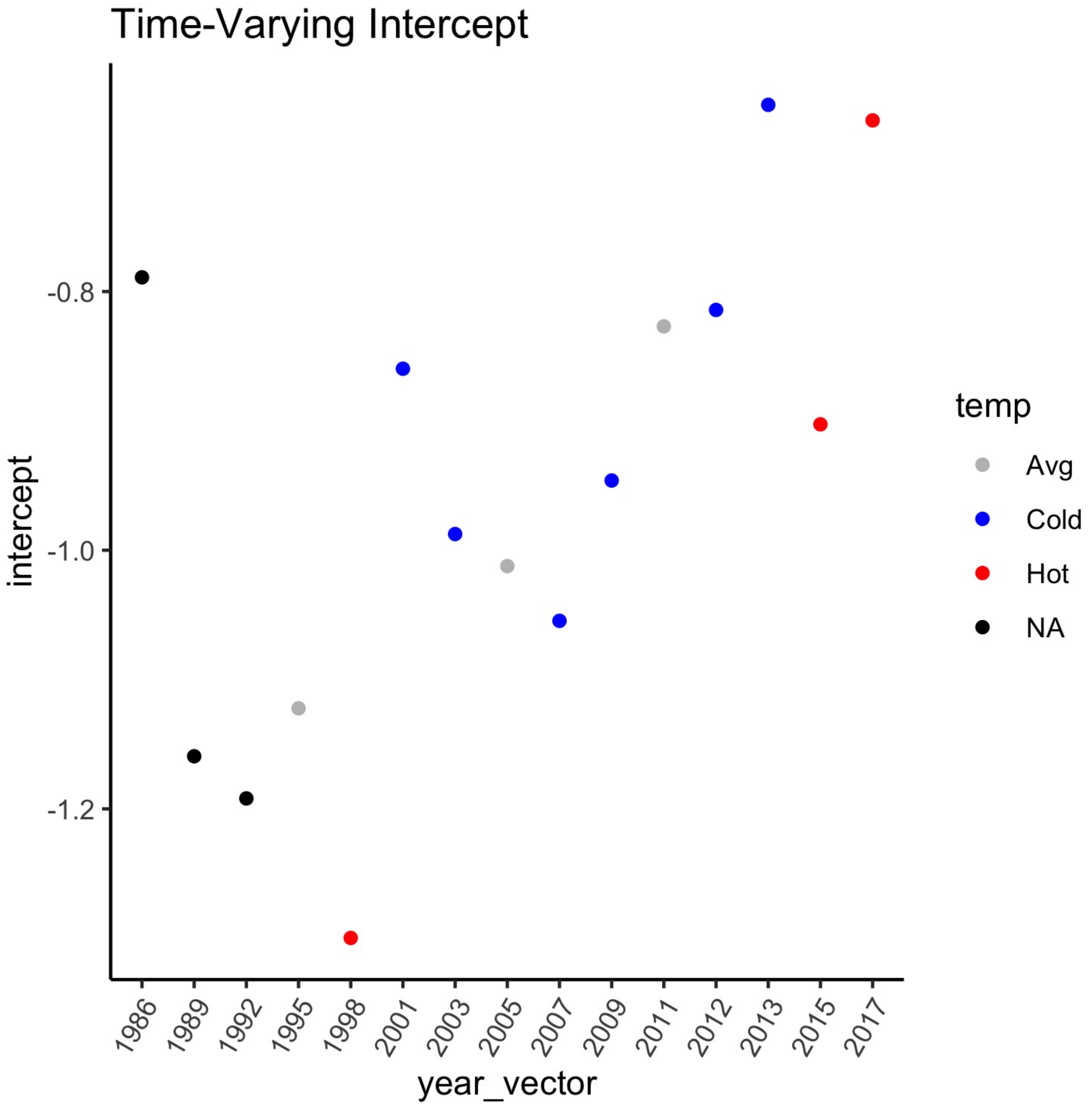


There is a very interesting spatial trend! It looks like the hake are lighter than average in areas nearby where freshwater meets the ocean (columbia river basin and san joaquin river basin) and a patch of heavier than average hake at the entrance (or exit?) of the strait of juan de fuca. Through quick search, it looks like there is a patch of greater primary productivity at the entrance of the strait of juan de fuca similar to where we see the patch of heavier than average fish (Davis, K. A., N. S. Banas, S. N. Giddings,S. A. Siedlecki, P. MacCready,E. J. Lessard, R. M. Kudela, andB. M. Hickey (2014), Estuary-enhanced upwelling of marine nutrients fuels coastal productivity in the U.S. Pacific Northwest, J. Geophys. Res. Oceans,119, 8778–8799)

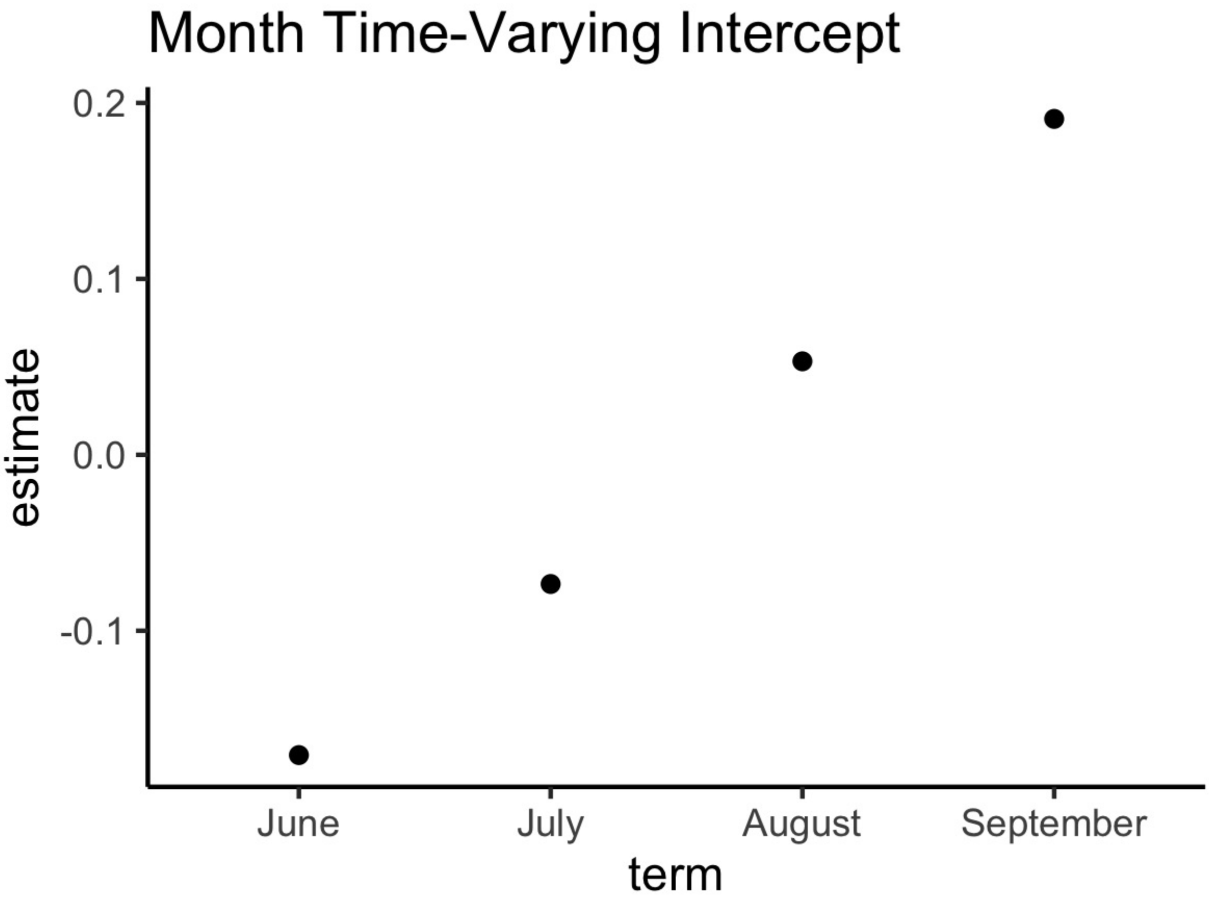

1986
1989
1992
1995
1998
2001
2003
2005
2007
2009
2011
2012
2013
2015
2017
55
50
45
40
35
Latitude
-135
-130
-125
-120
Longitude
epsilon_st
0.0
-0.5

Sept 26-30, 2022

Looking at the time-varying intercepts, there is quite a clear temporal trend revealing pacific hake are becoming heavier than average! The information on temperature anomaly is pulled from Malick et al. (2020). The trend doesn't appear to be strongly tied to temperature, at least when visualized this way.

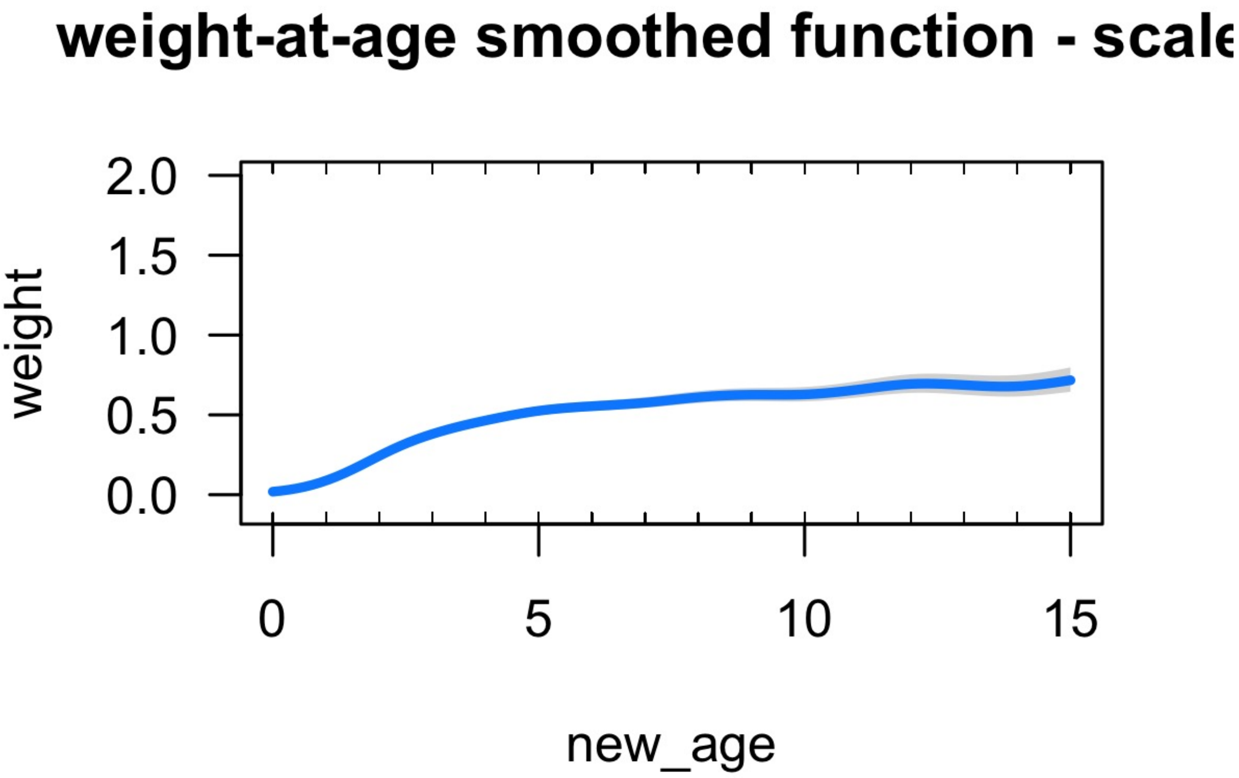


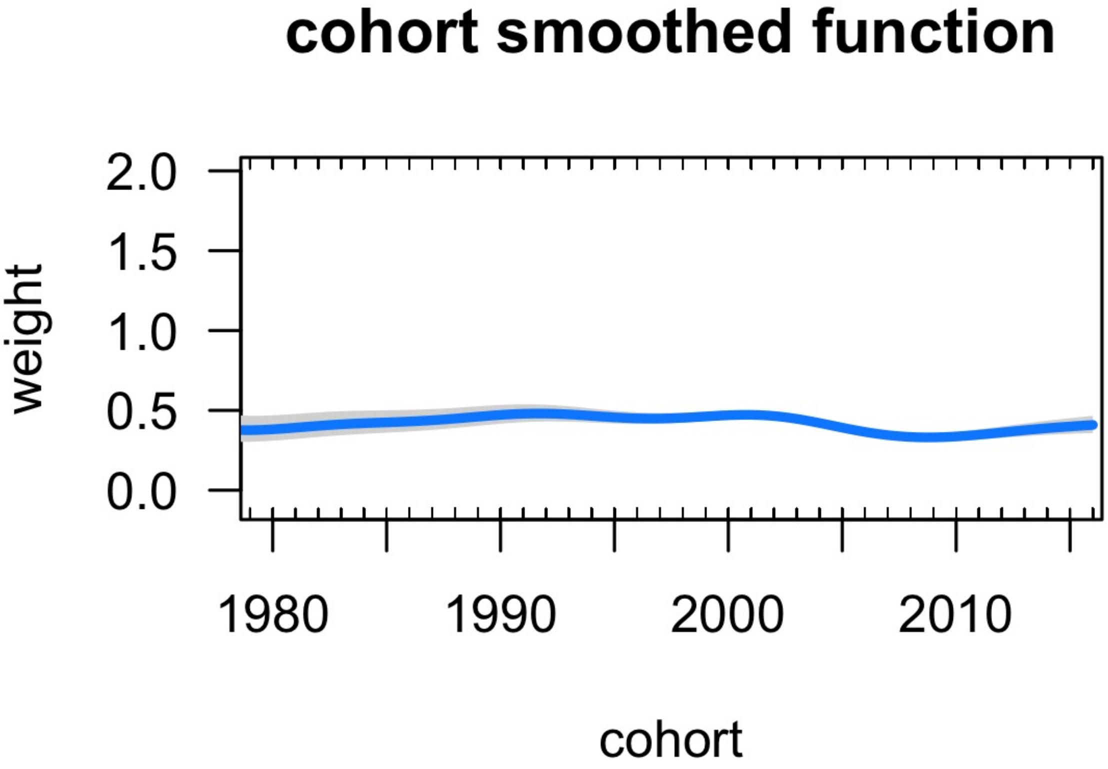
Malick et al. 2020 looked at whether the relationship between temperature and biomass remained stationary across life stages by splitting the data up into 3 age groups (age 2, 3-4, and 5+) and running the statistical model. Potentially something I can do...



When looking at the varying intercepts associated with month, there seems to be a linear increase according to the model. Previously, when just visualizing the data, there was a nonlinear trend in weight at age between months so we decided to treat catch_month as a random effect. This could be the result of uneven sample sizes which is accounted for as a random effect in the sdmTMB model. Might be worth switching cohort back to being a linear effect.

GAMS


weight-at-age smoothed function - scale
weight
2.0
1.5
1.0
0.5
0.0
0
5
10
15
new_age



The linear component of age is positive (~ 20) and the linear component of cohort is negative (~ -5). With age, that checks out (weight should be positively associated with age), but it seems as though there is a negative trend with cohorts - so more recent cohorts are trending lighter than average when compared to previous cohorts. This is interesting to think about in conjunction with the time-varying intercept, where hake are trending heavier than average through the time-series. However, there is greater uncertainty in more recent cohorts because of fewer years available to estimate weight-at-age. The standard deviation of the weights for each smoothing function is greater for age than for cohort, which I interpret as the extent of wiggliness.

After realizing that catch_month is has a linear effect on weight, I reran the model with catch_month as a linear predictor `weight ~ 0 + s(new_age) + s(cohort) + catch_month` with time varying intercept. I ran two versions of this model: spatial + spatiotemporal (m4.2) and just spatiotemporal (no spatial; m4.3). I did this because the spatial standard deviation (omega_s) was fairly low compared to the spatiotemporal standard deviation (epsilon_st) and one of the vignettes mentioned not to run a spatial model when the spatiotemporal SD was much larger than the spatial SD. When I ran those two new models, the AIC indicated that m4.2 was the best model, m4.3 was <1 AIC value larger so there wasn't too much of a difference butthis model had a few errors when looking at model diagnostics. The original model I was using where catch_month was a random effect was ~15 AIC values greater than the other models.

The only change that occurred in the outputs/coefficients when switching catch_month to a linear predictor was that the coefficient values for the time-varying intercepts shifted to smaller numbers, but the trend remained the same. Everything else remained the same and instead catch_month has a linear effect of 0.13.

Things to remember
- Cohort effects - is there density dependence? i.e. in years with high recruitment and consequently more

compeitition for resources, do those cohorts remain lighter than average?
- Pacific Hake also have spatial structure (larger, older fish travel more northward) - be mindful of how that might influence what we see. Is that captured in the spatial sd? or in catch_month (which is associated with space because sampling occurs more northward each month)

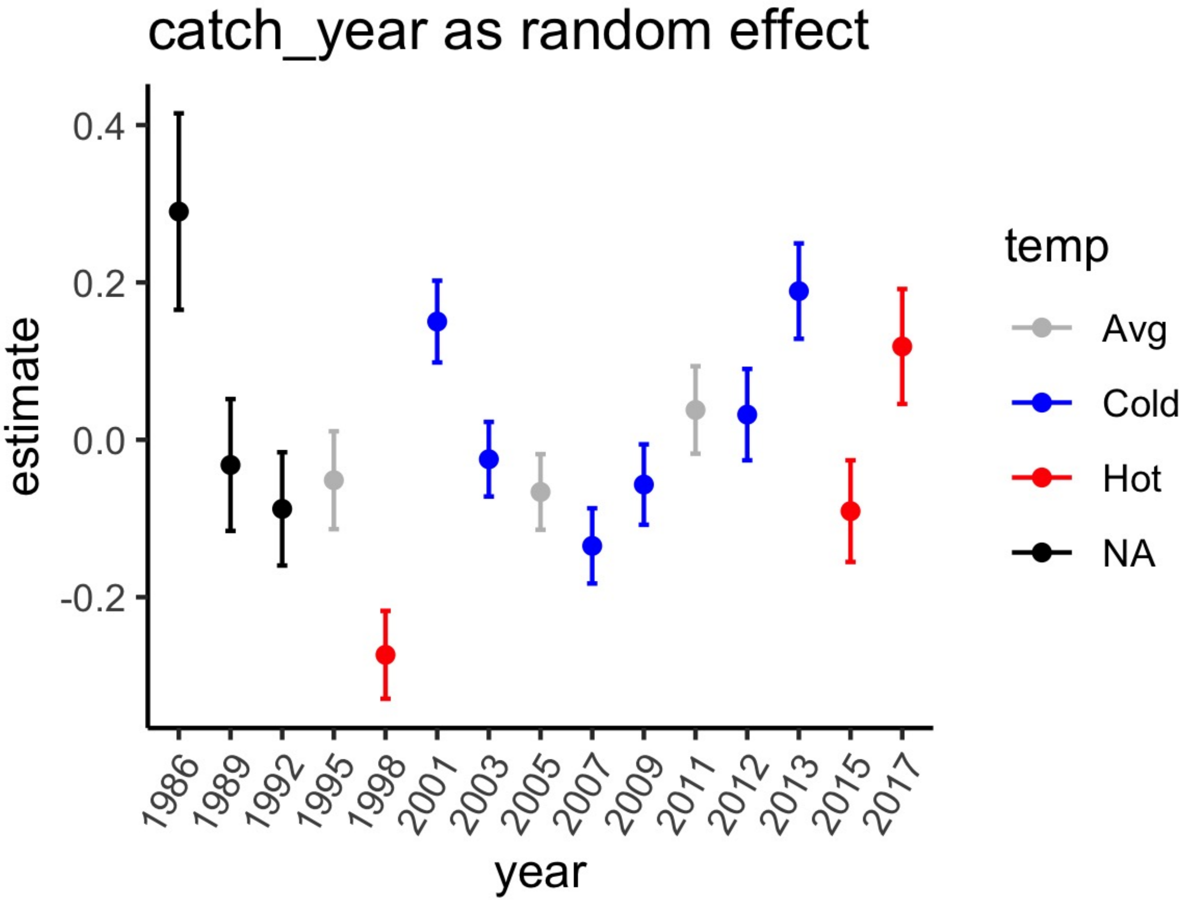
Model Validation? - AIC - well-documented biases with mixed effects models - k-fold cross validation - tmbstan package to sample from joint posterior, evaluate accuracy of laplace approximation or perform posterior predictive checks - residuals: MCMC avoids statistical issues but is slower - simulate.sdmTMB() can simulate from fitted models and sdmTMB_simulate() can simulate entirely new data to ensure identifiability, evaluate bias and precision in estimates, or avaluate consequences of model misspecification.

There are also codes for each ship that sampled. It looks like there are 6 unique ship codes. Might be worth including ship_code as a covariate to account for ship-ship variation?

In terms of predicting over the spatial domain, the reason it is not working right now is because each spatial coordinate is being predicted by all of the years, months, cohorts, and ages. What might need to be done is instead figure out potential drivers for spatial variation which could be included into the model, so the predictors only have one value at each spatial coordinate.

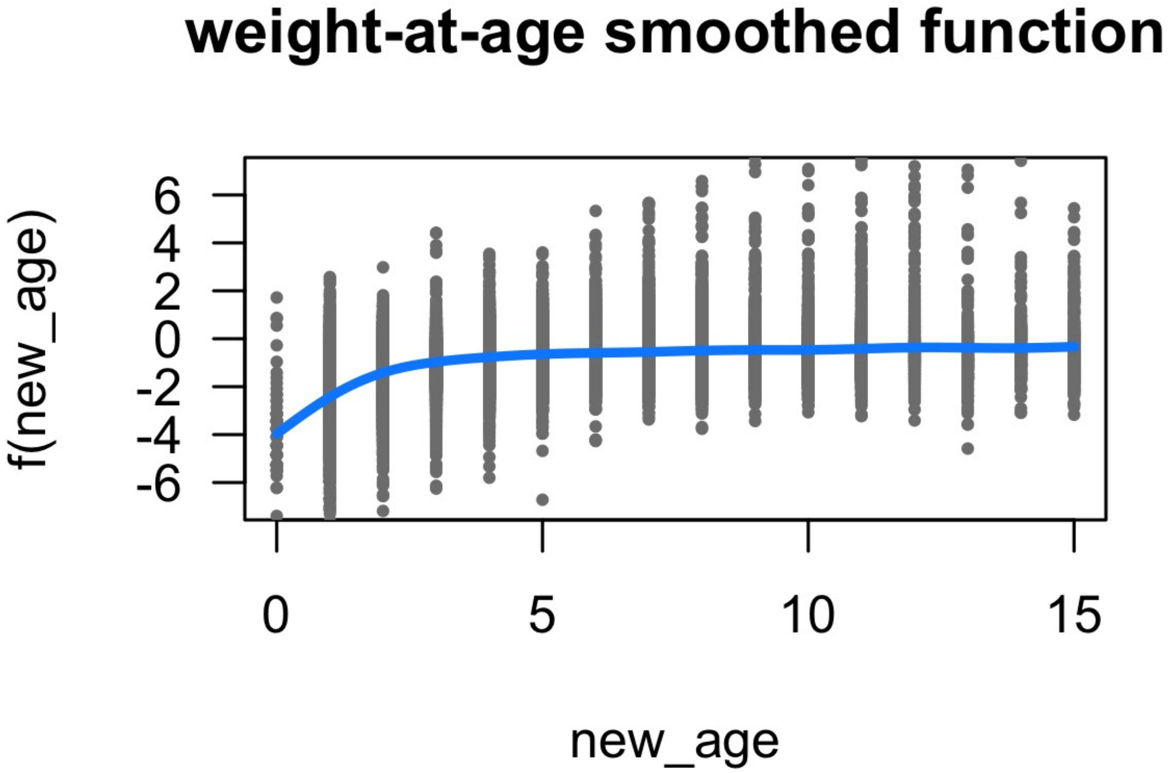
Notes for Meeting with Kristin - negative time-varying intercepts - Intro to sdmTMB vignette also has time-varying coefficients that are all negative. I also kinda wonder if this has something to do with how they are calculated. In the output, it shows `(Intercept)-1991` as the parameter name, so is it subtracting from the "current" year? - Originally I have the intercept as a time-varying parameter (random walk), but I tried other ways to vary the intercept - `as.factor(catch_year)` (i.e. IID) - did not converge - `(1 | catch_year)` random effect

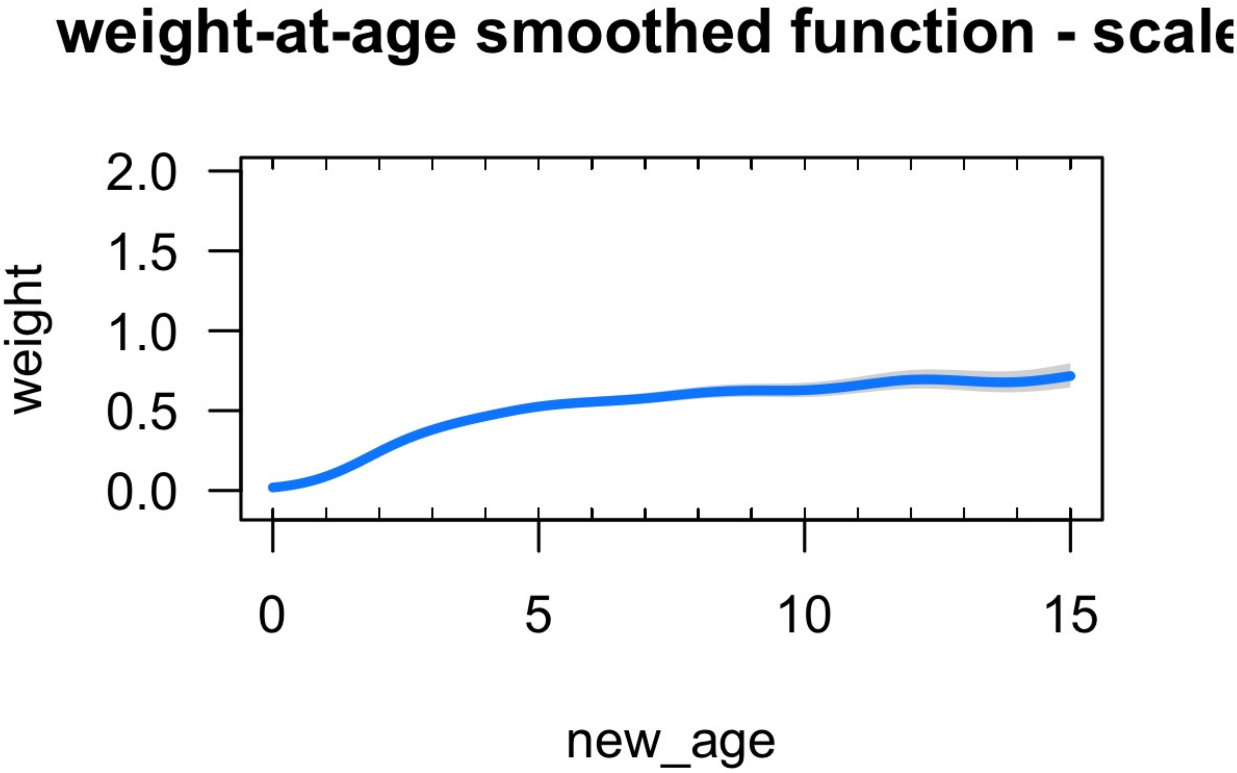
When we assume catch_year is a random effect

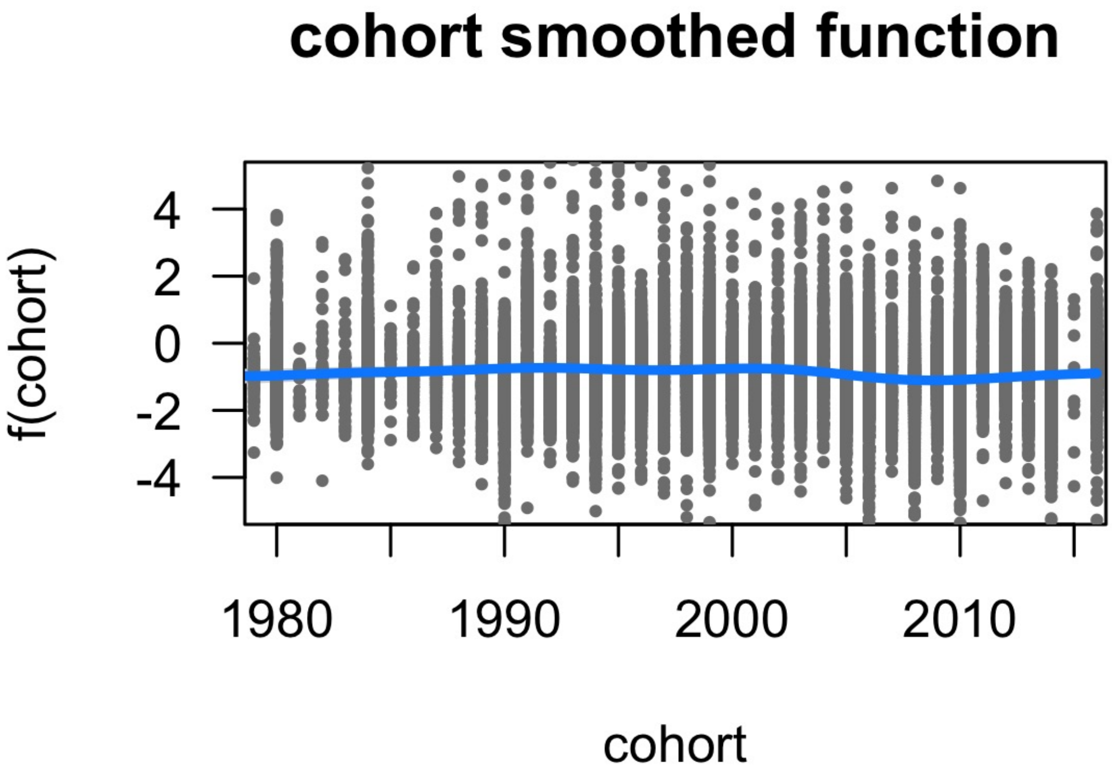


So, I think the question is, should we assume time as a random effect or as a random walk? The reason why I switched to time as a random walk is because in order to make predictions, “time needs to be modeled” (i.e. not a random effect)

For the GAMs, I scaled them according to the response variable “weight” because I thought that would be easier to interpret. Below are both the scaled and unscaled GAM plots. I reran these plots using the newest model with catch_year as a random effect


weight-at-age smoothed function
f(new_age)
6
4
2
0
-2
-4
-6
0
5
10
15
new_age


weight-at-age smoothed function - scale
weight
2.0
1.5
1.0
0.5
0.0
0
5
10
15
new_age


cohort smoothed function
f(cohort)
4
2
0
-2
-4
1980
1990
2000
2010
cohort